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Improving the economic recovery of oil and gas through data analysis and optimal flow measurement

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Abstract

Although our energy supply is not longed purely wedded to fossil fuels but produced from a wider range of sources such as solar or wind these days, there remains a considerable challenge in providing affordable and reliable energy to all households around the world. The oil and gas industry as the biggest supplier to address this demand for energy still plays the major role in the energy market and has an extensive influence on the energy price. Increasing the economic efficiency of the processes and the energy-producing systems in this industry can therefore significantly contribute to securing energy affordability. With the ever-increasing application of data in the oil and gas industry, its availability and accuracy are of vital importance in hydrocarbon field management and increasing the economic recovery of oil and gas. Perhaps the most important type of data in the oil and gas industry are production flow rates which is a basis of decisions in hydrocarbon field management. In many cases, however, the production data of wells contain large flow measurement uncertainties or are not available continuously due to the shortcomings of the traditional methods of flow measurement or estimation that are still used in the industry. This research has investigated the effects of these uncertainties on the economic recovery of oil and gas reservoirs and tried to propose solutions for mitigating them. In order to do that, the uncertainties in the production data have been statistically analysed and the effects of the frequency of flow tests on the accuracy of allocation calculations and hydrocarbon accounting have been investigated (Chapter 3). The case studies in the analysis showed up to 80 million dollars reduction in the annual cost of allocation uncertainties when flow tests were undertaken weekly instead of monthly in an oil field with 36 production wells. Based on the statistical analysis, a method that includes the application of an artificial neural network has been proposed to find the minimum frequency of flow tests required to achieve a desired allocation error (Chapter 4). The effects of the uncertainties of flow data on history matching and well testing (Chapter 5), which are two main exercises contributing to reservoir management, have been investigated subsequently. The results show the significance of the negative effect of systematic errors and therefore the importance of regular calibration and maintenance of flow meters, installing multi-phase flow meters on individual wells, and recording the data downhole instead of on the surface.

Keywords: oil and gas, data analysis, flow measurement, reservoir management, allocation, machine learning, artificial neural network, reservoir simulation, modelling, uncertainty, hydrocarbon accounting, history matching, well testing

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Nomenclature

Symbols and abbreviations:

AE%	Allocation error (%)
$\mathrm{AF_k}$	Allocation factor for well *k*
ANN	Artificial neural network
ATP	Actual total production (STB)
BU	Build up test
$\mathrm{CP_{\Delta t_{i+1}}}$	Cumulative production over the *(i+1)th* time interval (STB)
$\mathbf{D_{ref}}$	Vector of reference production data (STB/day)
$\mathbf{D_{sim}}$	Vector of the production data from the simulator (STB/day)
DD	Draw down test
$\mathbf{DF}$	Vector of dispersion factors
$\mathrm{E_{ETP}}$	Estimated total production error
ETP	Estimated total production (STB)
K	Permeability (mD)
MER	Maximising economic recovery
MPFM	Multi-phase flow meter
m	Total number of contributing wells
n	Number of data points
P	Pressure (psia)
$\overline{\mathrm{Q}}$	Average flow rate of the well during the test time (STB/day)
$\mathrm{Q_i}$	The *i-th* measured flow rate data point during the test (STB/day)
$\mathrm{Q_{t_i}}$	Production flow rate at the time t_i (STB/day)
q	Flow rate (STB/day)
$\mathbf{RND}$	Vector of random numbers between zero and one
RSD	Relative standard deviation

ref	Reference data
S	Skin factor
S	Softmax function
SD	Standard deviation
$SD_{\mathbf{RND}}$	Standard deviation of the **RND** vector
STB	Standard barrel
TP_{field}	Total production of the entire field (STB)
T	Tansig function
TPM	(Flow) test per month
t	Time (day)
test	Test results
VFM	Virtual flow meter
W	Weight
x	A single data point
$\bar{x}$	Average of all data points
ΔP	Pressure change (psia)
$\Delta P'$	Derivative of the pressure change
ΔPn	Normalised pressure change
$\Delta Pn'$	Derivative of normalised pressure change
Δt	Change in time
$\boldsymbol{\lambda}$	Inter-porosity flow coefficient
σ	Standard deviation
ω	Storativity ratio

Table of contents

List of figures

List of tables

Chapter 1: Introduction

1.1 Background

More than 11% of the population in England live in fuel poverty according to the UK Department for Business, Energy, and Industrial Strategy (Annual fuel poverty statistics report 2018) and the Office of Gas and Electricity Markets (State of the energy market 2018). This is equivalent to 2.55 million households in England who cannot afford to keep their houses warm during the winter. The statistics in some other areas of the world show even worse situations as a result of the high price of energy and poor economies (Bouzarovski and Petrova 2015; International Energy Agency (IEA) 2019a). Figure 1.1 shows a world atlas of total primary energy supply (TPES) per capita. TPES is an indication of energy consumption. Comparing this figure with the Gross Domestic Product (GDP) per capita statistics of countries around the world (United Nations 2019) shows that those countries which are at the bottom of energy consumption tables are normally the same countries that have the weakest economies. The entire aforementioned argument implies that energy affordability is still a major problem in our world. Therefore, at the same time as moving towards clean sustainable energy sources, the affordability of energy also needs to improve.

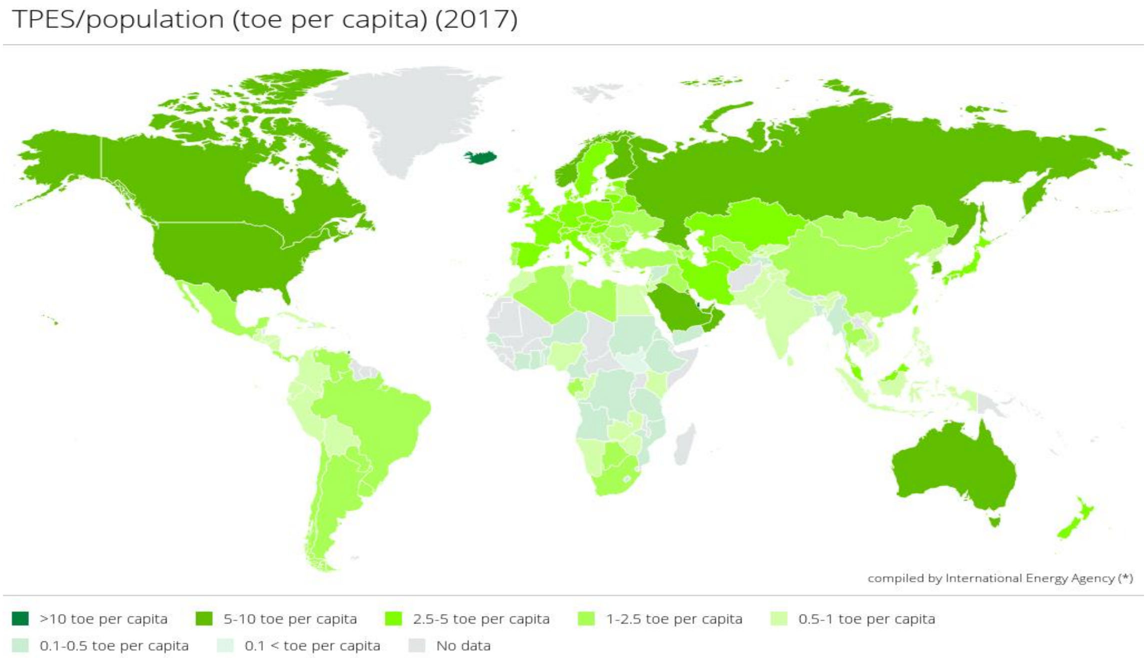

Figure 1.1: World atlas of total primary energy supply (TPES) per capita (toe stands for a tonne of oil equivalent) (International Energy Agency (IEA) 2019b).

Although our energy supply is now produced from a wider range of sources, such as photovoltaic and thermal solar, the tides or wind and for some countries, a nuclear power base load, there still remains an important role for the oil and gas industry in the energy sector. Figure 1.2 displays the contribution of different sources in primary energy consumption around the world. Oil is still the largest energy source making over a 34% contribution and natural gas is in the third place providing almost 24% of the total consumption and increasing. It means the energy sector is still largely dependent on the oil and gas industry which supplies more than half (58%) of global primary energy. This dependency means that the oil and gas industry remains in a very important position in determining the price of energy and its security.

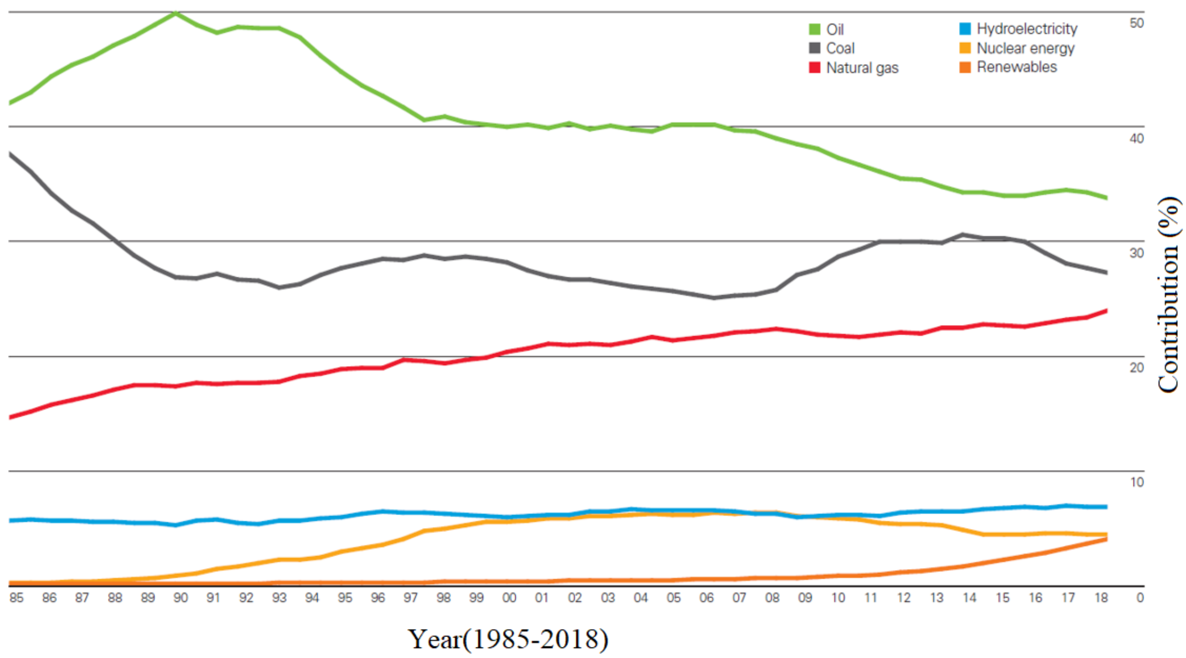

Figure 1.2: The contribution of different sources in primary energy consumption around the world (British Petroleum 2019). Oil is still the biggest energy source.

Not only do changes in the price of hydrocarbon products directly affect consumers, but also they have an immediate influence on the price of energy from other sources, such as renewables. One main factor in determining the price of energy is therefore the daily price of oil. Figure 1.3 shows the changes in the price of oil from 1861 to 2018. Although the figure shows peaks over time, the overall price trend shows an increase, especially after 1973 Gulf War that a sharp increase is observed. While world events have created a significant effect, mostly temporary, on the oil price, the main reason for the current higher price compared to the past is the energy demand increase, in spite of the global economic turndown in 2010. Therefore, to maintain a reasonable price for energy and to maintain its affordability, especially for poorer societies, the energy supply needs to increase as fast as demand. This is, however, not the only factor that contributes to keeping energy affordable. Increasing the economic efficiency of energy-producing systems is another important element.

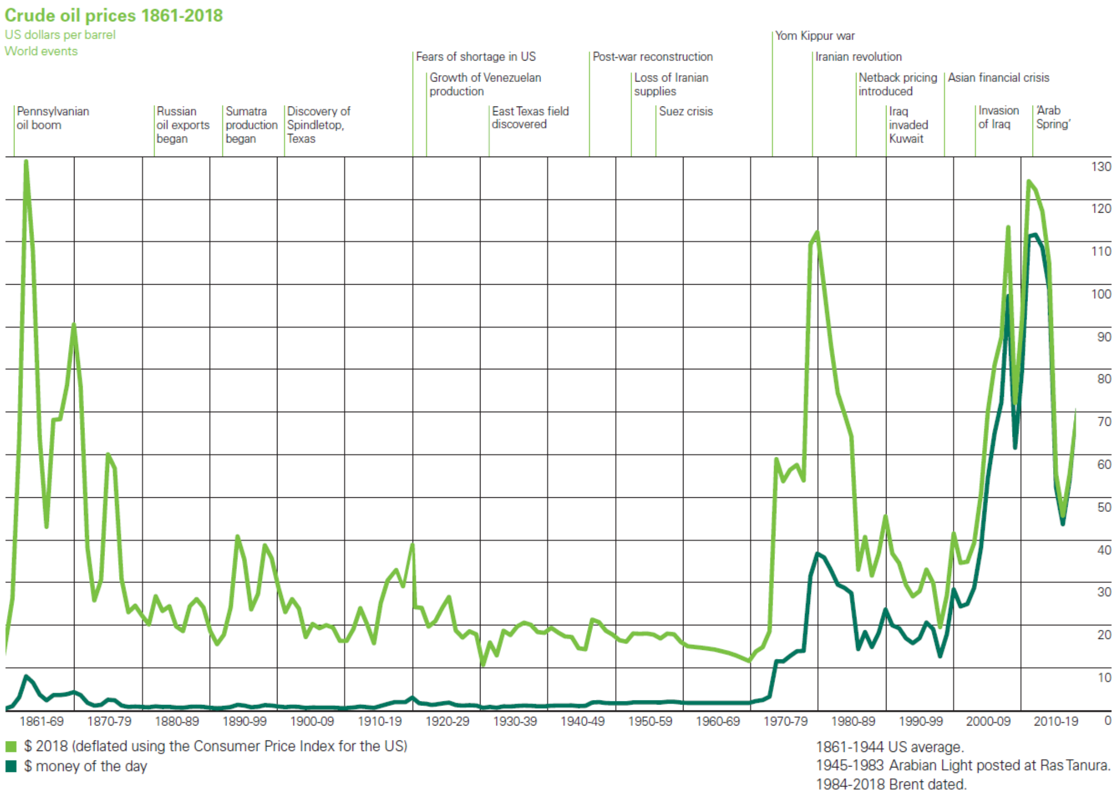

Figure 1.3: Changes in the price of oil from 1861 to 2018 (British Petroleum 2019). The total trend in the price increasing especially after 1973.

Since the oil and gas industry is still the main global supplier of energy, any method that can increase the efficiency of the production processes in this industry can reduce the price of energy and ameliorate energy poverty. Higher efficiency oil and gas production also reduces the costs of operating companies and increases oil and gas reserves (i.e. the amount of oil and gas that is financially feasible to be recovered considering production costs and the hydrocarbon price). Hence, higher efficiency not only increases the total recovery of oil and gas, but also, more importantly, the total ‘economic’ recovery of oil and gas. Economic recovery is referred to the financial benefits of oil and gas production after considering all of its costs.

Maximising economic recovery of oil and gas within existing laws and regulations (Energy Act 2016; Environmental Protection Act 1990; Petroleum Act 1998), such as regulations in regard to protecting the environment or health and safety, is the aim of oil and gas producing companies. An efficient field management programme must therefore be undertaken by companies to achieve these goals. Hydrocarbon field management, especially in its modern form, includes dealing with a large amount of data coming from different sources, such as production facilities, simulators, formation evaluation tests, and rock and fluid laboratories. Decisions about how to operate a field are made based on these sets of data. An important element of this data (perhaps the most important) is the production flowrates from wells in a reservoir that has a fundamental role in the reservoir management, production optimisation, decision-making process, hydrocarbon accounting, and tax payment. The accuracy of the production data can therefore directly (in hydrocarbon accounting) or indirectly (in reservoir management) affect the economic recovery of oil and gas. Larger measurement or estimation uncertainties in the flow rate data mean a higher cost of production for oil and gas companies and a lower energy production efficiency. This lower efficiency can potentially have an influence on the energy market and the final cost of energy for consumers. As a consequence, mitigating the uncertainty in the production flow rate data of oil and gas fields can play a role in increasing the economic recovery of oil and gas and providing affordable energy to the market.

1.2 Thesis overview

1.2.1 Aims and objectives

The production from wells in the oil and gas industry mainly includes three fluids: oil, gas, and water. Operators normally have to deal with multi-phase flows that add to the complexity of any flow measurement exercise. The uncertainty in the recorded production flow rates is therefore large in many hydrocarbon fields around the world. This uncertainty, as mentioned above, can potentially increase the cost of production and reduce the economic recovery of oil and gas. The aim of this research is to provide recommendations and methods to increase the economic recovery of oil and gas through mitigating the uncertainty in the production data. The exact effect of this uncertainty on the economic recovery, however, is not clear. To achieve the aim of this research, therefore, a thorough understanding of the influence of these uncertainties on the whole process of oil and gas production was required. The main research questions of this thesis are

- Which exercises in the oil and gas production process can potentially be affected by flow measurement uncertainties?
- Are the effects of the uncertainties on these processes significantly costly and can they reduce the economic recovery of oil and gas?
- Are there any methods that can mitigate the uncertainties or their cost and ultimately increase the economic recovery of oil and gas?

Hence, the objectives of this research to attain its aim and answer the questions are

- Determining hydrocarbon production exercises in which flow measurement data is employed widely
- Finding potential direct and indirect links between production flow rate uncertainties and the economic recovery of oil and gas in these exercises
- Estimating the cost of the uncertainties for operators by undertaking case studies, simulations, and data analysis
- Presenting recommendations for cost reduction based on the data analysis

The research was focused on the role of flow measurement uncertainties in hydrocarbon accounting and reservoir management. In hydrocarbon accounting, the uncertainties have a direct and clear effect on the operating costs (OPEX) of oil and gas companies, while in reservoir management their effect is indirect and subtle.

1.2.2 Thesis structure

Different techniques are employed in the industry to monitor or estimate production flow rates. The most common method is still undertaking occasional flow tests on individual wells, although the application of other methods, such as multi-phase flow meters (MPFM) or virtual flow meters, has increased recently. In Chapter 2 of this thesis, these different methods of flow measurement or flow rate estimations in the oil and gas industry are explained. The common errors and uncertainties which are associated with flow rate data are also discussed. This research has had two main phases; the first phase on the effects flow measurement uncertainties on allocation and hydrocarbon accounting and the second phase on the effects of these uncertainties on reservoir management. The results of the first phase are presented in Chapters 3 and 4 and the results of the second phase are discussed in Chapters 5. Chapter 3 is dedicated to statistical analysis of the uncertainties and investigating their effects on allocation and hydrocarbon accounting calculations. Based on the analysis in Chapter 3, an artificial neural network (ANN) was developed and trained and the results of the application of this ANN for reducing the errors of allocation calculations are presented in Chapter 4. Chapter 5 is written on the role of flow measurement in reservoir management. The first section of Chapter 5 details effect of flow measurement errors on history matching which is a main sub-process of reservoir management. The second section of the chapter, however, discusses this role in well testing, another main element of reservoir management. Conclusions and recommendations of this PhD research are summarised in Chapter 6.

Chapter 2: Flow measurement in the oil and gas industry

2.1 Introduction

Flow measurement has an important role in the oil and gas industry. Flow meters are widely used to measure the flow of producing fluids from the reservoir or the injection of fluids into it. The data from the meters is used for different purposes, such as hydrocarbon accounting and reservoir management. In the case of hydrocarbon accounting, the amount of hydrocarbons which is transferred between operators or sold need to be recorded with an acceptable accuracy to enable operators to perform financial calculations and governments to determine taxation revenues. In many cases, producing fluids from different wells or oil fields are commingled and the total outcome is retrospectively allocated to the owners. Allocating the flow in an equitable way requires accurate flow measurement data. Therefore, flow meters are vital for hydrocarbon accounting in the oil and gas industry. Moreover, the production or injection data measured by flow meters can be analysed and used to secure a better management over the reserves. Since proper management can increase the recovery of oil and gas, the collected flow measurement data also has an indirect effect on the recovery factor of oil and gas reservoirs. In this chapter, the role of flow measurement in the oil and gas industry is discussed. In the following sections, different methods of flow measurement in the oil and gas industry are presented. Then, the application of flow meters in fiscal measurements, custody transfer, and hydrocarbon accounting are explained. Finally, the important role of flow measurement data in history matching, optimisation and reservoir management is elaborated.

2.2 The role of flow measurement in hydrocarbon accounting

Hydrocarbon accounting is also referred to as hydrocarbon production reporting or allocation. Although it can include a variety of activities in the oil and gas industry, the main aim of hydrocarbon accounting is to track and measure reservoir producing fluids, especially when they are being transferred from one owner to another or determining the share of each owner from the total production when production from different fields or wells is commingled. The amount of tax that should be paid to the government by the operator is also determined through hydrocarbon accounting. The accuracy of the measurements and methods which are used in the hydrocarbon accounting process is important since a failure in providing acceptable measurements results in a non-fair distribution of the revenues between the owners. In addition, it can prevent sellers from being able to determine the correct price of the hydrocarbon that they are delivering to the next owners. Therefore, different guidelines have been developed in different countries to specify the required measurement accuracies for hydrocarbon accounting. For instance, in the United Kingdom, the details of the regulations for hydrocarbon measurements have been provided by the Oil & Gas Authority (2015). It is not just flow meters that control the accuracy of hydrocarbon accounting, however. Other software and hardware facilities are also involved in this process. Therefore, in addition to the accuracy of flow meters, the accuracy of the employed methods, calculations, and facilities are also important in the entire process. The role of these factors in the accuracy of hydrocarbon accounting can be different from one case to another depending on the design of the production facilities, the number of owners, or the necessity of back allocation. In the case where there is just one owner and the measurement is performed for equitable custody transfer, the role of flow meters is of the highest importance. However, when there is commingled production from different owners and back allocation is needed to determine the share, the methods of allocation have vital importance in addition to the accuracy of the flow meters. Chapter 3 and 4 of this thesis focus on hydrocarbon accounting and allocation and have presented a method to reduce their uncertainty.

Custody transfer involves the activities which are necessary to determine the price of hydrocarbon production fluids which are transferred from a seller to a buyer. The terms ‘custody transfer’ and ‘fiscal measurement’ are often interchangeable. However, in some references, fiscal measurement has been defined as being more general than custody transfer. In those references, fiscal measurement includes both custody transfer and allocation.

Allocation (or back allocation) is the act of determining the share of each source when the producing fluids from different sources are mixed. The sources are normally for different owners which makes allocation necessary to determine the income of each. Section 2.4.3 of this chapter explains more about allocation techniques.

2.3 The role of flow measurement in reservoir management

Many hydrocarbon reservoirs are located deep under the surface of the earth. This means that the reservoir is an unknown system for us, there is a limited access to it, and gathering information about the reservoir is difficult. Different methods have been developed and employed to obtain information from hydrocarbon reservoirs. Among these are seismic (Bacon, Simm and Redshaw 2007; Vermeer 2002), reservoir rock and fluid sample analysis (Schön 2015; Tiab and Donaldson 2015), formation evaluation (Darling 2005), and well testing (Bourdet 2002; Horne 1995; Lee 1982). All the information that can be obtained from all of these methods, however, cannot give an accurate image of the reservoir. Knowing the characteristics of a hydrocarbon reservoir such as its size, the initial amount of oil in place, the reservoir rock and fluid properties (e.g. porosity, permeability, fluid viscosity, and fluid density), location of faults, type and location of the reservoir boundaries, and characteristics of aquifers is necessary for the operating companies. It enables them to have an integrated management over their hydrocarbon reservoirs and maximise their income from the reserves. Although these characteristics are measured or estimated using the aforementioned methods, there is still a vast uncertainty in the knowledge they provide from a reservoir (Babak and Deutsch 2008). Therefore, operators record and analyse any type of reservoir data that can help them reduce the uncertainty in the reservoir knowledge. Production data (i.e. oil, water and gas production flow rates, and downhole or wellhead pressure) can be analysed in an inverse problem to calculate the characteristics of a reservoir (for instance in well testing) or to mitigate the uncertainty in the reservoir model through history matching. History matching, well testing and other analyses based on production data are inverse problems. In a forward problem, by knowing the parameters of a system, the outputs of the system can be estimated. In contrast, in an inverse problem the characteristics of the system are unknown (Kern 2016; Kirsch 2011; Oliver, Reynolds and Liu 2008). In such a problem the outputs of the system are used to calculate the parameters of the system. Forward and inverse problems are shown in Figure 2.1.

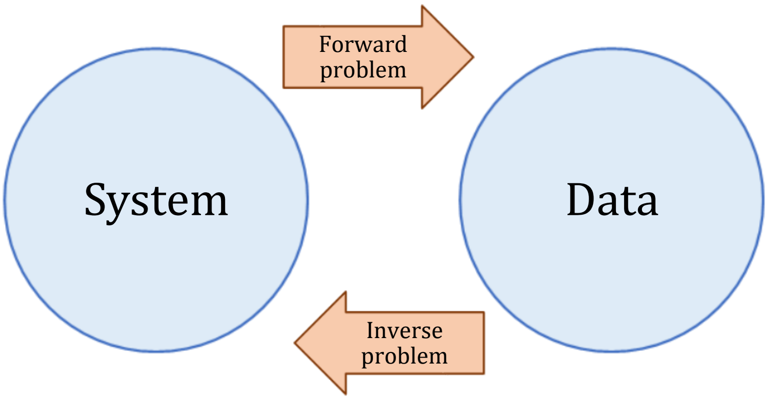

Figure 2.1: Forward and inverse problems. History matching and well testing are two inverse problems in reservoir engineering.

Proper reservoir management requires the solving of many inverse problems and dealing with numerous uncertainties. Therefore, the quality of the output data is of vital importance. Production data of the reservoir (oil, gas, and water flow rates and pressure data) is the main output of the reservoir system. Therefore, the data needs to be measured properly or estimated by using appropriate methods, then recorded for later analysis. In order to achieve this, different methods and technologies of flow measurement are used, such as single-phase flow meters, multi-phase flow meters (MPFM), virtual flow metering, and allocation. Moreover, the way that the measurement is undertaken and the interval between measurements vary in different oil and gas fields. The interval between measurements can vary from a near real time flow measurement, where multi-phase flow meters are used, to several weeks where regular production tests are undertaken using test separators. In addition, the hardware, software, and methods which are used have different accuracies. All of these factors affect the quality of the recorded data and can then indirectly affect reservoir management and hydrocarbon recovery.

Reservoir management is a complicated process involving setting targets, making decisions, implementing the decisions, recording the results, analysing the data, and then modifying the initial decisions (Satter, Varnon and Hoang 1994). The fundamentals of reservoir management have been presented in different publications (Al-Hussainy and Humphreys 1996; Satter, Varnon and Hoang 1994; Thakur 1996; Trice Jr and Dawe 1992). A recently introduced method referred to as Closed-Loop Reservoir Management (CLRM) is presented in the following section and has been employed in this research to show the role of flow measurement in reservoir management. Although CLRM is a relatively new method in reservoir management, several publications from different authors who have employed it can be found in the literature (Barros, Van den Hof and Jansen 2016; Hanssen, Codas and Foss 2017; Jansen et al. 2005; Jansen, Brouwer and Douma 2009; Lorentzen, Shafieirad and Naevdal 2009; Wang, Li and Reynolds 2009). The main advantage of the CLRM method over other management methods is that it has a standard procedure that clearly and simply shows the contribution of different components of reservoir management, including production data, to the entire process. This advantage makes it an appropriate method for investigating the effects of different parameters, such as the quality of data on the reservoir management. A schematic of CLRM which has been presented in the literature by Jansen, Brouwer and Douma (2009) is shown in Figure 2.2.

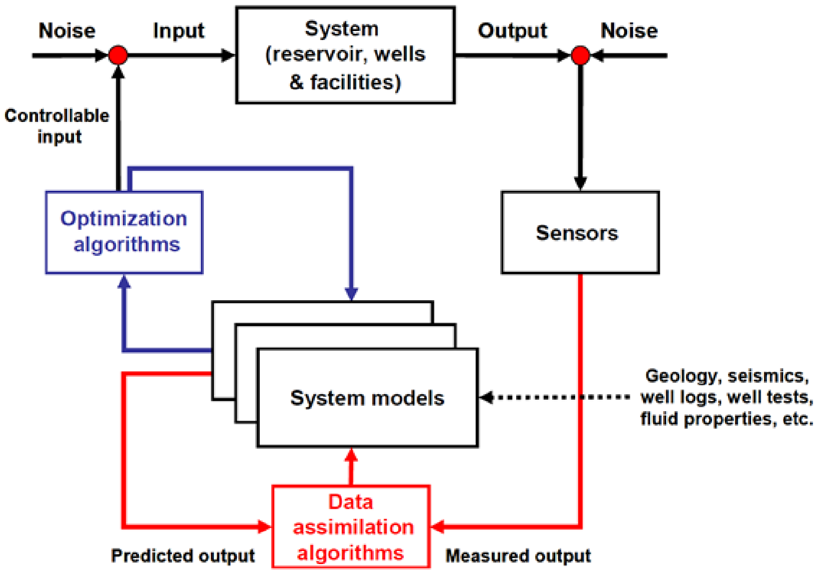

Figure 2.2: Closed-Loop Reservoir Management (CLRM) process (Jansen, Brouwer and Douma 2009).

The two main components in CLRM are the actual reservoir and the reservoir model. In order to manage the actual reservoir and meet the targets that have been set for the exploitation process, a reservoir model that properly represents the actual reservoir is necessary. The operators cannot examine their plans on the actual reservoir in a trial and error method since it will affect the production and recovery of the reservoir. In addition to that, since the life of a reservoir is normally of the order of tens of years, it takes a long time to see the results of their decisions on the actual reservoir and then modify them. Alternatively, a reservoir model based on the characteristics of the reservoir can be built in a simulator. Many decisions and modifications are made based on the simulations that are performed on the reservoir model. If the reservoir model is similar to the actual reservoir, the results of the simulations will be similar to what actually happens in the reservoir in the future. Otherwise, the model cannot represent the actual reservoir. In such a case, the decisions made based on the model will not be the best decisions for the actual reservoir and will make it difficult for the operators to set proper goals and reach their desired targets. Therefore, as has been shown in Figure 2.2, all the information that is obtained from geology, seismic, well logs, well tests, and reservoir fluid and rock sample analysis is employed to build a better reservoir model. However, since the information obtained from the reservoir is vastly uncertain, the reservoir model still cannot represent the actual reservoir accurately. This uncertainty in the model needs to be reduced and the model modified over time. This process is performed in the sub-loop of history matching. In the history matching loop, the outputs of the model are compared to the measured outputs of the reservoir. Based on the comparison, the model is then modified in an iterative procedure. There is also another sub-loop for reservoir optimisation. During the optimisation, the optimum values for production parameters that can be controlled by the operator, such as production rates or the location of the new wells, are determined. The CLRM itself has a main loop that connects all of the components in the reservoir management process. The loop enables the reservoir management to change from an intermittent process to a dynamic, near continuous one. It relates the outputs of the reservoir to its inputs. In other words, the decisions as to how to control the input parameters are made based on the outputs of the system or the way that the reservoir reacts to changing input parameters. The effect of the outputs of the reservoir on its inputs shows the importance of the quality of the recorded data. Any possible errors in the recorded outputs affect history matching, the reservoir model, optimisation, and finally the inputs (controls) of the reservoir. Therefore, the performance of the reservoir and its recovery factor are influenced by the quality of the recorded data. Since the production flow rates are important parts of the reservoir output, one main focus of this research is on the role of flow measurement in reservoir management and hydrocarbon recovery.

Flow measurement errors in hydrocarbon accounting is important for oil and gas companies because they can directly affect the share of each owner from the production of the field. When it comes to reservoir management, however, the effect of flow measurement on the income of the companies is not direct and clear. Operators normally deal with large uncertainties in the reservoir itself. In many cases, the effect of the uncertainties in the flow measurement data is ignored in comparison to other large uncertainties in the process or in the reservoir. The focus of many researchers and professionals has therefore been on quantifying and reducing the uncertainties in the reservoir characteristics (Ahmadinia et al. 2019; Babak and Deutsch 2008; Oliver and Chen 2011). Since production data is used in mitigating uncertainties in the reservoir model (e.g. uncertainties in porosity, permeability, reservoir size, reservoir shape, and location of faults), however, the uncertainties in the data can impact this process. Therefore, investigating the effects of these uncertainties on the reservoir management is necessary. This issue has been addressed in this research.

In the following sections, some main parts of a reservoir management process that can significantly be affected by flow measurement uncertainties are discussed. The two main sub-processes of reservoir management, history matching and optimisation, in addition to well testing, are briefly explained in this chapter and the role of flow measurement in them has been elaborated. In Chapter 5 of this thesis, the effects of flow measurement errors on history matching and well testing which are two main exercises of reservoir management that directly employ flow measurement data have been discussed in details, respectively.

2.3.1 History matching

As stated previously, history matching is an inverse problem and its aim is to mitigate the uncertainties in the reservoir model. Since there are limitations in the methods that are currently available to gather data from the reservoir, there is normally a large uncertainty in the initial reservoir models, which are built based on the data. The data is gathered through geological investigations, seismic, well logging, well testing, and reservoir rock and fluid sample analysis. All of these sources of information have limitations and the accuracy of the technology and the methods which are used affect the accuracy of the obtained data. As an example, since the number of wells that are drilled in a reservoir is limited, the number of areas of the reservoir in which rock and fluid samples can be taken is restricted. The characteristics of these samples, such as porosity, absolute permeability, relative permeability, fluid viscosities, and fluid densities are measured in laboratories. However, since actual reservoirs are heterogeneous in their characteristics, the measured values in the laboratory based on a limited number of samples do not necessarily represent the characteristics of the entire reservoir. The measured values of a parameter or average of them may be used in the simulator to build the entire reservoir model, or a part of it, but such a model cannot accurately represent the actual reservoir. Due to heterogeneity, the value that is used as the average value of a parameter in the model is normally different from the actual average value of that parameter in the reservoir.

Therefore, the initial model cannot forecast the future production accurately and it needs to be modified. History matching is widely used in the oil and gas industry to modify reservoir models. In order to do that, the actual production data of the reservoir (observed data) is compared with the simulated production data obtained from the model. If the two sets of results do not match, the model is modified in an iterative procedure. In each iteration, the results of the model are again checked against the observed data. If the match is not acceptable the model is modified again, and the iterative procedure is continued until an acceptable match is achieved. Figure 2.3 shows the iterative process of history matching.

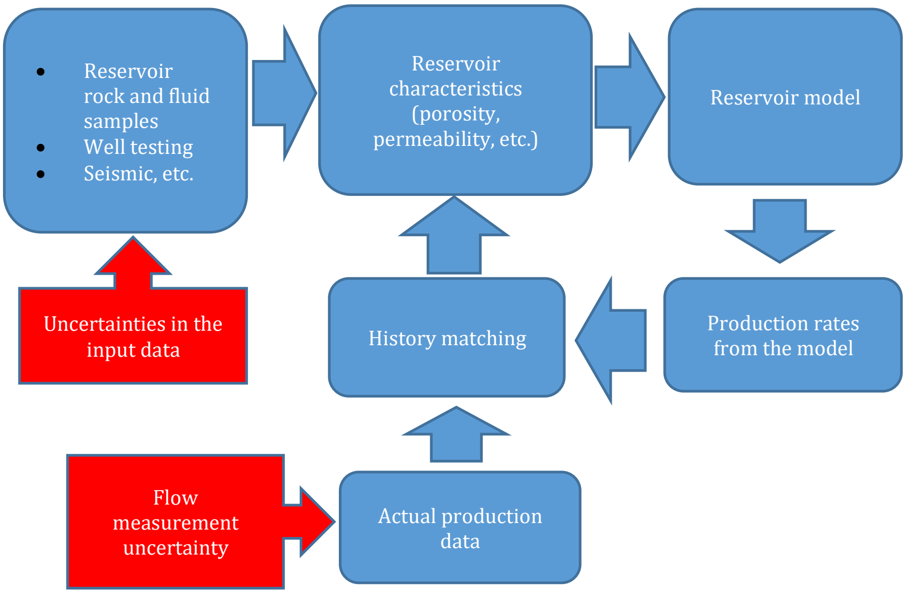

Figure 2.3: The iterative procedure of history matching. The aim of history matching is to reduce the uncertainties in the reservoir model.

The loop of history matching is employed to reduce the uncertainties in the measured or estimated input data (Figure 2.3). Although other uncertainties such as those related to the model selection or governing equations also exist, the history matching case study in this research will focus on input parameters such as porosity and permeability because they are very important in reservoir engineering calculations and there are typically large uncertainties associated with their estimated values. Flow measurement data (observed data) has an important role in this process. The data is used as the reference for history matching to show how accurate the results of the model are. However, similar to the input data of the model, there is normally an uncertainty in the flow measurement. In other words, the reference data that is used to reduce the uncertainty in the model, normally has some uncertainty in itself. This uncertainty has a potential effect on the performance of the history matching and the accuracy of the model. Since there are normally large uncertainties in reservoir models, the uncertainty in the observed data is ignored in the oil and gas industry in many cases. However, depending on the method of flow measurement protocol being used, this uncertainty can be large and its effect can be significant. Therefore, it is necessary to investigate the effect of flow measurement uncertainties on history matching. Evaluating this effect can assist the operators in improving their methods of flow measurement and data collection and subsequently obtain more accurate results from history matching and their reservoir models. This is one aim of Chapter 5 of this thesis.

2.3.2 Optimisation

Optimisation is the second sub-loop in CLRM (Figure 2.2) after the sub-loop of history matching. The aim of an optimisation process is to achieve the possible peak economic recovery of the reserves. An objective function, such as the ultimate hydrocarbon recovery or net present value (NPV), is therefore chosen that needs to be maximised within the existing constraints (Wheaton 2016). This is undertaken through an optimisation process by finding the best operating conditions or values for the controllable inputs of the reservoir. Some examples of these controllable inputs are the development plan (Vasantharajan, Al-Hussainy and Heinemann 2006), such as the location and number of the new wells and platforms (Bangerth et al. 2006), the water injection rates in a water flooding process (Lien et al. 2008; Peters et al. 2010), and the gas injection rate in a gas lifting exercise (Bahadori, Ayatollahi and Moshfeghian 2001; Wilson 2015). The optimisation process, however, directly or indirectly through the history matching exercise is effected by the uncertainties in the recorded production data. Flow measurement data and the outputs of the history matching (such as the modified reservoir model) are the elements employed in the process of optimisation. Any uncertainty in these elements can therefore deter the process from finding the optimum operating conditions and values for the controllable inputs of the reservoir and, as a result, decrease its ultimate economic recovery.

2.3.3 Well testing

Well testing (or pressure transient testing) is another practice in the oil and gas industry that significantly contributes to reservoir management through providing information from the reservoir. It is an inverse problem (similar to history matching) through which some characteristics of a reservoir and its wells, such as the average permeability, drainage area, storativity, distance to faults, and the shape of the drainage area, are calculated. The fundamentals of different well testing techniques have been discussed by Stewart (2011), Chaudhry (2004), and Zhuang (2012).

The main parameters of a well measured during a well test and then analysed are pressure and flow rates. Pressure is normally measured both at the bottom of the wells (bottom-hole pressure or BHP) and at the surface (well head pressure or WHP). Flow rates, however, are typically measured using flow meters at the surface through standard flow measurement techniques common in the industry. Some of these techniques have been explained in Section 2.4. The most common technique is still using a test separator and single-phase flow meters. Since flow rate data plays a fundamental role in well testing analysis, any uncertainty in the data can also have a potentially significant effect on the analysis. It means these uncertainties can indirectly affect the reservoir management process and eventually reduce the economic recovery of oil and gas from the reservoir. Figure 2.2 illustrates the role of well testing in CLRM in developing the reservoir model. The potential effects of flow measurement errors in well testing on reservoir management and hydrocarbon economic recovery are discussed in Chapter 5.

2.4 Methods of flow measurement in the oil and gas industry

Different flow measurement techniques and technologies are used to monitor up-stream production flow rates in the oil and gas industry. The flow measurement method for each field is chosen based on many factors, such as the required accuracy, production conditions (e.g. stability and water cut), number of owners, and the associated costs. In the following sections, some of these flow measurement methods and the related technologies are explained.

2.4.1 Flow meters

Flow meters are widely used in the oil and gas industry and they are the basis of production monitoring systems in all oil and gas fields. Although virtual flow metering and allocation methods are explained in separate sections below, even those methods are not fully independent of actual flow meters. The application of flow meters, as a result, has a long history in the oil and gas industry and their measurements are still considered the most accurate production flow rate data in the industry (compared to other available methods). There are two general types of flow meters: single-phase flow meters and multi-phase flow meters (MPFM).

2.4.1.1 Single-phase flow meters

Monitoring the flow rate of a multi-phase stream is a complicated practice. On the other hand, the technology for single-phase flow measurements has been available for a considerable time and is ubiquitous. Hence in the majority of oil and gas fields, the multi-phase flow production of wells is first separated into single-phase flow streams of oil, gas, and water, respectively and then each stream measured by single-phase flow meters. Although the application of multi-phase flow meters has recently increased, the measurements of single-phase flow meters are still considered more reliable when a high accuracy is needed, such as in fiscal measurement and custody transfer. The main types of single-phase flow meter which are currently used in the oil and gas industry are differential pressure, ultrasonic, Coriolis, vortex, thermal, positive displacement, and turbine. In the following sections, the first three mentioned types are explained briefly.

2.4.1.1.1 Differential pressure flow meters

Flow meters that work based on a differential pressure mechanism have been available for more than a century and are still the most widely used flow meters in the industry (Liptak 1993). They include an element that reduces the cross section of the pipe available to the flow and therefore create a pressure difference that can be measured. This pressure difference measurement can subsequently provide the flow rate of the phase through the associated equations (Baker 2016). Some of the most common types of differential pressure flow meter are venture meters, orifice meters, and flow nozzles. These flow meters are suitable for gas or liquid. Their mechanism is simple and there is no limitation on the pipe size. They, however, cause a larger pressure drop compared to some other flow meters such as ultrasonic. Another disadvantage is that the fluid density is required in equations, that they cannot measure themselves. The fluid density, therefore, should be measured or estimated independent from the flow meter. It can potentially introduce extra measurement or estimation errors to the flow measurement data. They are also intrusive that means production needs to be stopped while they are installed.

2.4.1.1.2 Ultrasonic flowmeters

The application of ultrasonic flow meters has recently increased in the oil and gas industry because of some advantages they have over other types of flow meter. They measure the time required for ultrasonic energy pulses to travel through the flowing fluid. The in-line (intrusive) type ultrasonic flow meters are accurate enough to be used in both gas and liquid custody transfers. They create less pressure drop compared to some other types of flow meter, such as differential pressure, and they can be produced in a non-intrusive design. Non-intrusive ultrasonic flow meters are typically referred to as the ‘clamp-on’ type. Although they have a lower accuracy than the in-line type, their installation does not need a process shut down (Liptak 2003).

2.4.1.1.3 Coriolis flow meters

The technology of Coriolis flow meters is relatively new even compared to ultrasonic flow meters. Their main advantages that differentiate them from the other flow meters is that they directly measure mass flow rate (while other flow meters normally measure volumetric flow rate) and the density of the flowing fluid. These two parameters are measured based the principle of the Coriolis force which is produced in their oscillating systems (Padmanabhan 2012). The flow meter includes vibrating tubes which change their frequency and Coriolis force balance when a fluid flows through them. When the fluid enters the flow meter, it is divided between two tubes (a strait and a curved tube). These two tubes oscillate with different speeds and create sine waves with different frequencies. The time delay between the sine waves (that shows the relative speed of the tubes compared to each other) is directly proportional to the mass flow rate of the fluid. Although Coriolis flow meters have these inherent unique advantages, they are more expensive and there are limitations on their operational flow range (Liptak 1993).

2.4.1.2 Multi-phase flow meters (MPFM)

One of the challenges of the oil and gas industry is dealing with the complications of multi-phase streams. Although combining separators and single-phase flow meters enables operators to measure the flow rate of each phase, it is technically and financially not possible to have all these facilities for each production well. In some specific cases the available space is limited, such as on offshore production platforms, therefore placing even a single test separator is sometimes a challenge. In many oil and gas fields, the production of individual wells is therefore not measured or measured only occasionally through flow tests. Not only does this approach introduce large uncertainties to the available data, but it also increases the reaction time of operators to production flow rate changes because of the lack of real-time production data. Moreover, there is an increasing problem of ageing reservoirs meaning that there are more instabilities in their production caused by water or gas breakthrough. The need for a real time production monitoring system is therefore felt more than at any time in the past. As one response to this need, MPFMs were brought into use in the late 20th century. MPFMs can provide real-time measurements of two or three phase flows. Their technology has developed significantly since they were firstly introduced to the industry, leading to a higher measurement accuracy, lower prices, less health and safety problems, and a wider range of applicability. Some of the advantages of using MPFMs over traditional methods of flow measurement in the oil and gas industry are:

- Providing real-time continuous data of production leading to less uncertainty and faster reactions by operators to production changes
- Occupying less space; a factor which is important, especially in offshore fields
- Enabling the operators to monitor flowrates remotely
- Facilitating the monitoring of individual wells

On the other hand, there are still some difficulties with the cost of MPFMs which can be up to hundreds of thousands of dollars that should be added to the cost of their regular calibration and maintenance. Categorising MPFM types is not as easy as single-phase flow meters since an MPFM includes different units which are responsible for the measurement of different characteristics of the flow, such as phase densities, phase velocities, phase ratios, and total mass flow rate. Each flow meter, as a result, is a combination of different technologies and employs a variety of methods to obtain phase flow rates. Detailed information about the technology of MPFMs and their measurement methods has been presented by Falcone, Hewitt and Alimonti (2009), Falcone et al. (2002), Corneliussen et al. (2005), and Thorn, Johansen and Hjertaker (2012).

2.4.2 Virtual flow metering

Virtual flow meters (VFM), as it is apparent from their name, are not physical flow meters. They are software packages that estimate flow rates based on the data they receive as their input that comes from the production facilities. The required input data can vary from a VFM to another but in many cases, it includes temperature, pressure, fluid properties, and characteristics of the production facilities such as choke opening. Despite the recent advances in developing more accurate VFMs by employing data science and machine learning methods (AL-Qutami et al. 2018; Andrianov 2018; Cramer et al. 2011; Shoeibi Omrani et al. 2018), VFMs are still not considered a replacement for physical flow meters. In most cases they are employed as a backup for physical flow meters or used where no flow meter is available.

2.4.3 Allocation

As mentioned above, single-phase flow meters are still widely used in the oil and gas industry. These flow meters need to be installed after the separation unit. Since it is financially not possible to have a separator for each individual well, the production of several wells is transferred to the same separation unit and then the total flow rates of oil, water and gas are measured by single-phase flow meters. It means these flow meters do not provide the flow rates of individual wells, but only provide the total combined production of all of them. Operators, therefore, use an extra separator other than the ones in the separation unit to measure the production of individual wells periodically. This separator is called a test separator and the periodic flow measurement exercise is called a flow test, a well test, or a daily test. The continuous data of total production and the non-continuous data of flow tests are subsequently combined in allocation calculations to estimate the production of each individual well over the time between two flow tests. Different methods of allocation calculations can be found in the literature. Some of these methods are proportional allocation, uncertainty-based allocation, equity-based allocation, and allocation by process modelling (Energy Institute 2012). In the following sections, proportional and uncertainty-based methods that are the most common methods of allocation in the industry are explained.

2.4.3.1 Proportional allocation

Proportional allocation is a very common and easy to understand method. In this method, the total production is allocated to different producers in proportion to their allocation factors. Allocation factors are estimations of the contribution of each producer based on periodic flow tests or the measurements of upstream flow meters.

$$AF_k = \frac{B_k}{\sum_{i=1}^{m} B_i} \quad 1 \leq k \leq m \tag{2.1}$$

$$Q_k = AF_k . Q \tag{2.2}$$

where AF_k denotes the allocation factor for producer k, B_k is the quantity (i.e. flow rate) measured or estimated for producer k, m shows the total number of producers, Q represents the quantity that should be allocated, and Q_k is the quantity allocated to producer k.

This method of allocation has been used in this research for hydrocarbon accounting calculations in Chapters 3 and 4.

2.4.3.2 Uncertainty-based allocation

Uncertainty-based allocation (UBA) is a more complicated method compared to the proportional method. This method considers errors in the system for allocating quantities. Therefore, it is considered a suitable method that provides equitable results where there is a significant difference between the accuracy of data coming from different sources. UBA gives more weight to the data with a higher accuracy. There are different approaches and formulations for UBA. As an example, Energy Institute (2012) has presented the following equations for UBA where m number of sources are contributing to the total production.

$$I = Q - \sum_{i=1}^{m} B_i \tag{2.3}$$

$$\beta_k = \frac{U_k^2}{\sum_{i=1}^{m} U_i^2} \qquad 1 \le k \le m \tag{2.4}$$

$$Q_k = B_k + \beta_k \times I \tag{2.5}$$

where I stands for the total imbalance in the system, Q denotes the quantity (i.e. total production) that should be allocated, B_k is the quantity measured or estimated for producer k, m shows the total number of producers, β_k represents the calculated weight for producer k, Q_k is the quantity allocated to producer k , U_k is the absolute uncertainty of the estimated or measured quantity for producer k. U_k is therefore equal to the error specification of the flow meter used on producer k or it is the error of the estimation method.

2.5 Flow measurement uncertainties and errors

Uncertainties and errors are inevitably a part of observed data. Observation methods, employed technologies, and even human error affect the scale of uncertainties. In the oil and gas industry, the uncertainty in the observed data could potentially be high. Oil and gas reservoirs are complicated heterogeneous systems of multi-phase flows under high pressure. Reservoir production can include up to four phases (Oil, gas, water, and sand) and the flow rates can have large fluctuations. Therefore, measuring the multi-phase flow production of reservoirs under these circumstances can be quite difficult. In addition to the technical difficulty, the required capital (CAPEX) cost for installing flow meters that can work under these conditions is high and their regular calibration and maintenance (OPEX) is difficult and costly. The capital and operating cost of flow meters are the financial constraints that sometimes prevent operators from developing a measurement system that can monitor individual wells. All of these factors create a vast uncertainty in the observed flow measurement data from oil and gas reservoirs. The new improvements in the knowledge of reservoir management have made the importance of accurate flow measurement in the oil and gas industry clearer. Operators normally undertake regular production tests and the application of multi-phase flow meters in the oil and gas industry has increased. However, even where the new technologies and methods of flow measurement are employed, flow measurement errors are unavoidably a part of the collected data. Flow measurement errors are typically divided into two categories: random errors and systematic errors.

2.5.1 Random errors

Random errors occur in both directions (positive and negative) and they shift the value of the measurement by a random amount. The causes of random errors are normally unpredictable and sometimes unknown. They can be caused by the environment, flow meter limitations or many other factors. Since it is currently impossible to control them all, random errors are inevitably a part of any measurement data. Therefore, if the same flow rate is measured several times, different values for it are obtained. In contrast to systematic errors, random errors can be analysed statistically. They can be explained mathematically in terms of their mean (Eq. 2.6) and standard deviation (Eq. 2.7).

$$\overline{x} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right) \tag{2.6}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}} \tag{2.7}$$

where, $\overline{x}$ is the mean of all measurements, x_i refers to the value of the *i-th* measurement, n denotes the total number of measurements, and σ refers to the standard deviation of the measurement values.

In most cases, random errors have a Gaussian distribution (Figure 2.4). In Figure 2.4, $\overline{x}$ is the mean of the population and σ is its standard deviation.

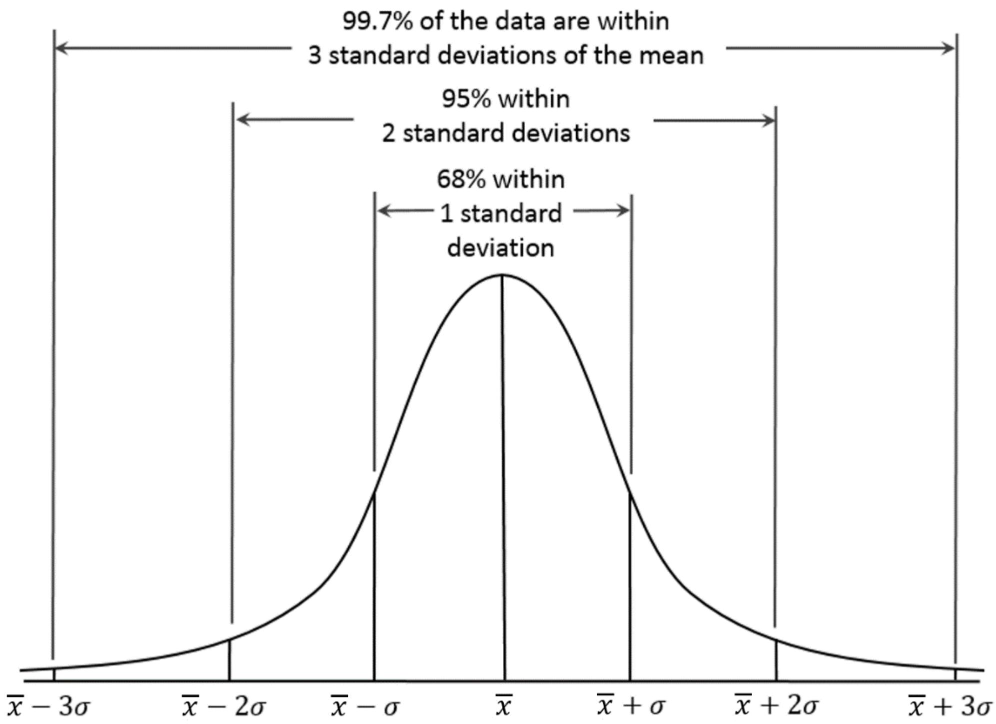

Figure 2.4: The Gaussian distribution. Around 68% of the measurements are within one standard deviation from the mean of the measurements (Lyman and Longnecker 1988).

As illustrated in Figure 2.4, the Gaussian normal distribution has a symmetrical plot and the axis of the symmetry is where the mean is located. In other words, the distribution of the errors on both sides of the mean is so that if they are averaged, the average value will be equal to the mean. This average value is often close to the true (actual) value of the measured quantity. Therefore, although performing a measurement without any random errors is not possible, the measured error for any quantity can be reduced by repeating the measurement and averaging the values. However, performing several measurements for the same quantity is not possible in many cases in the oil and gas industry due to the dynamic nature of the processes in this industry. Another method that can decrease random errors is through increasing the precision of flow meters (Tombs et al. 2006). Introducing new technologies of flow measurement by different companies has resulted in the development of more precise flow meters with smaller error specifications. However, installing these new meters normally entails a high capital cost. Therefore, it is important to gain a full understanding of the effect of random errors on the oil and gas industry to be able to decide if paying such a capital cost is worthwhile.

2.5.2 Systematic errors

Systematic errors normally occur just in one direction. They often have a constant value, or their value is a constant proportion of the quantity being measured. In these terms, systematic errors are divided into two general categories:

Zero setting error (offset error): when the quantity being measured is zero but the measurement instrument shows another value except zero. This error can be reduced or eliminated by calibrating the meter. However, environmental factors can cause meters to go out of calibration over time (Liptak 1993). Therefore, meters need to be recalibrated regularly to prevent this type of error in the recorded data.

Multiplier error (scale factor error): this error occurs when the meter reads a larger or smaller value than the actual quantity values and the measure value is proportional to the actual value. In other words, if a constant number (multiplier) is multiplied in the measured values, the actual values are obtained. The changes in the conditions of the environment in which the meter is operating can cause such an error. For instance, when the temperature increases, the length of a metal metre ruler is increased as a result of its material expansion. Therefore, the ruler will have a multiplier error in measuring the length and reads any measured length smaller than what it actually is. Meters, therefore, need to be used under the conditions (e.g. pressure and temperature) which are recommended by the manufacturer.

Although systematic errors typically have a pattern, detecting them is quite difficult. Moreover, systematic errors have a non-zero mean. Therefore, in contrast to random errors, they cannot be reduced by averaging all the measurements. Despite all of these difficulties, however, there are some approaches that can help minimise systematic errors. Careful and regular calibration and maintenance of flow meters, accepting their limitations and using them under the conditions suggested by the manufacturers are some of these approaches. In addition, operators need to be trained in their use by the manufacturers. Human error is categorised under systematic errors in some references. The accuracy of the data recorded can be increased if the operators of the flow meters are well trained.

2.5.3 Possible states of errors for a flow meter

In terms of systematic and random flow measurement errors, a flow meter can have different states. Figure 2.5 illustrates all of these states.

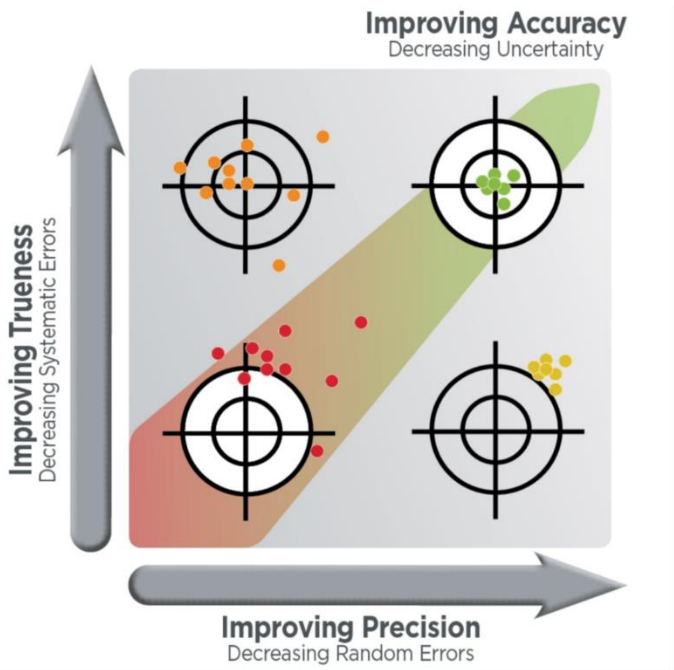

Figure 2.5: All possible states of a flow meter in terms of its precision and trueness.

Figure 2.5 has two axes; precision as the horizontal axis and trueness the vertical, respectively. In technical terms, when the precision of a meter increases, random errors in the measurements decrease. Recorded data of a precise meter have a good repeatability. It means if the measurement is repeated several times for the same quantity using the same meter, the obtained values are close to each other. In the opposite case, if the measurement is repeated using a meter with a lower precision, the recorded data will be more divergent. As shown in the right-hand side of Figure 2.5, the data points are dense and close to each other while in the left-hand side of the figure the data points are scattered due to the low precision. As the figure suggests, however, a high precision does not necessarily mean that the average of the recorded data represents the true value of the measured quantity. In low trueness, the average of the measurements is not close to the actual value of the quantity even if the meter is precise. In other words, systematic errors in the data deviate the average of measurements from the actual value. Trueness is therefore defined as the qualitative estimate of systematic errors in the measurements from a flow meter. Another term used frequently in the technical literature is ‘accuracy’. Accuracy is the estimate of both random and systematic errors in a set of recorded data. Therefore, to improve the accuracy of a flow meter both precision and trueness of the flow meter need to be increased.

In terms of precision and trueness, a flow meter can have a state in the range that has been shown in Figure 2.5. The state of the flow meter (or the accuracy of any measured or estimated data set) can be one of the four cases that have been written bellow, as well as any other state between them.

1. High precision, high trueness (top right state in Figure 2.5)
2. High precision, low trueness (down right state in Figure 2.5)
3. Low precision, high trueness (top left state in Figure 2.5)
4. Low precision, low trueness (down left state in Figure 2.5)

Chapter 3: Uncertainty analysis in allocation and hydrocarbon accounting*

Although the application of multi-phase flow meters has recently increased, the production of individual wells in many fields is still monitored by occasional flow tests using test separators, as mentioned in Chapter 2. In the absence of flow measurement data during the time interval between two consecutive flow tests, the flow rates of wells are typically estimated using allocation techniques. Since the flow rates do not remain the same over the period between the tests, however, there is typically a large uncertainty associated with the allocated values. In this chapter, the effect of the frequency of flow tests on the estimated total production of wells, allocation, and hydrocarbon accounting has been investigated. The frequency of flow tests plays an important role in reducing or increasing the uncertainties of the estimated production data. Having a correct understanding of the potential effects of these uncertainties on hydrocarbon accounting is necessary for developing any method of mitigating them and increasing the economic recovery of oil and gas. The contents of this chapter, therefore, are the fundamentals for Chapter 4 where an approach based on an artificial neural network has been presented to mitigate the uncertainties of the production data that is estimated through undertaking flow tests.

* The contents of this chapter have been extracted from the following paper:

Sadri, M. and Shariatipour, S. (2019) 'Mitigating allocation and hydrocarbon accounting uncertainty using more frequent flow test data'. Journal of Energy Resources Technology, 142 (4).

The candidate developed the methodology, undertook the required simulations, wrote the Matlab codes, analysed the results, and prepared the article. Seyed M. Shariatipour supervised the research.

3.1 Introduction

In many oil and gas fields, multi-phase production from different wells is commingled and then the total flow is transferred to a separation unit, where the individual phase flow rates are subsequently measured (Figure 3.1). The fiscal meters that measure these flow rates provide continuous data of the total field production which is used for hydrocarbon accounting purposes. However, in such fields, there is no continuous data available for individual well flow rates since their production is not metered separately. The only data of individual wells which is available in these cases is the result of occasional flow tests (sometimes referred to as 'well tests' or 'daily tests'). During a flow test, the production of a single well is guided into a test separator for a short time (typically a few hours) before it is mixed with the total production. The phase flow rates of the well are subsequently measured over the test time by single-phase flow meters at the individual outputs of the test separator. The test is normally repeated after a certain time interval for all wells in a field. The production data for individual wells is consequently intermittent and there is typically a gap of a several weeks to a few months between the next set of data points depending on the decision of the operators. Although the installation of multi-phase flow meters (MPFM) for individual wells has become more popular recently (Falcone, Hewitt and Alimonti 2009; Falcone et al. 2002; Theuveny and Mehdizadeh 2002), there are still many fields producing under the same circumstances as outlined. In such fields, the production data of an individual well is estimated by employing the results of the intermittent flow tests and the continuous measurements of the fiscal meters in a process which is called allocation or back allocation (Oil & Gas Authority 2015). The term 'allocation' is also used in other exercises in the oil and gas industry, such as gas lifting (Alarcón, Torres and Gómez 2002; Camponogara and Nakashima 2006; Nishikiori et al. 1995; Sukarno et al. 2009) or water injection (Azamipour et al. 2017). In this thesis, however, the term refers to the exercise defined above.

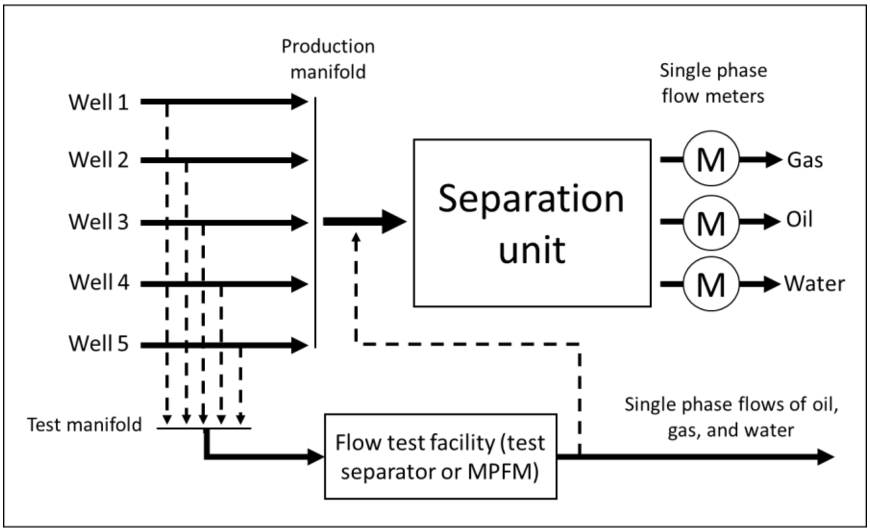

Figure 3.1: Schematic of the flow measurement facilities in an oil and gas field.

Different methods have been presented in the literature or employed in the industry for performing allocation calculations (Acuna 2016; Carpenter 2017; Cramer et al. 2011; Energy Institute 2012; Pobitzer, Skålvik and Bjørk 2016; Stockton and Allan 2012). The purpose of all of these methods is to estimate the production of a single well using the available data. A common approach which is widely used in the industry is to calculate allocation factors once flow tests are undertaken. The allocation factor of a well is the proportion of the total (commingled) flow that the well is producing. These factors are used to estimate the production of each well during the time between two tests and then are updated when the new test results are available. Therefore, in this approach, it is assumed that the allocation factors remain the same as the test time over the entire time taken to the next test. Since the duration of the test is just a few hours (e.g. six hours), and in many cases the flow tests are undertaken monthly, the allocation factors which have been calculated based on the data taken in less than 1% of time are assumed to be constant for the remaining 99% of the production period (Cramer et al. 2011). Production rate fluctuations, the natural decline of production, water or gas breakthrough, and many other similar phenomena in the reservoir, well, or production facilities, however, can change the allocation factors over time. Therefore, using constant allocation factors for a relatively long period of time such as a month seems to cause a large uncertainty in the estimated production data of individual wells. A number of researchers have therefore tried to find solutions for mitigating the allocation uncertainty. Cramer et al. (2011) suggested performing daily allocations using the estimations of virtual flow meters instead of discontinuous allocations based on flow tests. Although the performance of virtual flow meters has improved over time, their accuracy under all condition ranges is still not the same as actual flow metering facilities. Kaiser (2014) presented two different allocation methods using decline curve analysis and mixing ratios. Neither of the methods need flow test data. A thorough comparison of their accuracy with the accuracy of the traditional allocation method, however, has not been presented. Pobitzer, Skålvik and Bjørk (2016) proposed an algorithm that helps choosing the right meter and its place in the allocation process. Therefore, their focus was on optimising the allocation system setup for reducing the allocation uncertainty. Shoeibi Omrani et al. (2018) employed a machine learning technique to improve the accuracy of back allocation and virtual flow metering. They used pressure, temperature, choke opening, and the number of wells in the field as the inputs to their artificial neural network. Although the machine learning method looks promising in reducing the error, its inputs must be chosen carefully. Pressure and temperature are related to the flow rate but they might not be the best inputs to represent the fluctuations in the production. In this chapter, we have employed statistical parameters to quantify the characteristics of flow rate fluctuations. The resulting values can therefore be used as inputs to machine learning techniques (as it is shown in Chapter 4).

Coinciding with recent developments in multi-phase flow monitoring technologies (Kouba 1998; Lindsay et al. 2020; Liu et al. 2001; Teodorczyk, Karim and Tawfiq 1988), some researchers such as Theuveny and Mehdizadeh (2002) or Falcone, Hewitt and Alimonti (2009) suggested that the application of MPFMs can reduce the uncertainty in production data. Although the improvements in the accuracy of MPFMs make them one of the main potential alternatives to the traditional allocation method, the high cost of their application still remains a challenge in replacing test separators with them. It requires a considerable capital cost to install MPFMs on each individual well and also an operating cost for their regular maintenance and calibration. Moreover, the wells need to be shut during the installation process if the MPFMs are intrusive. Shutting the wells can cost the operators up to millions of dollars each day. All of these factors show the importance of a careful consideration of the cost of the uncertainties of the traditional allocation method and comparing it against the cost of using MPFMs. One aim of this chapter is to present an approach to estimate the potential cost of uncertainties of the traditional allocation method based on some statistical analyses of the test data.

Estimated production data is used for different purposes in the oil and gas industry. Therefore, not only can the uncertainty affect the allocation and hydrocarbon accounting calculations and the income of all involving parties, but also the process of reservoir management and the actual performance of the reservoir. Sadri et al. (2019) showed how the uncertainty in the flow measurement data of individual wells can affect a history matching practice and cause uncertainty in reservoir models (please see Chapter 5 for more details). The reservoir model is used in the decision-making process for the actual reservoir. Therefore, the production data uncertainty can potentially influence the performance of the reservoir and reduce its economic recovery indirectly. Marshall et al. (2019) investigated the effect of flow measurement uncertainty on the estimated recovery factor of reservoirs. They concluded that the uncertainty in flow measurement data can lead to incorrect estimated values for the recovery factor (please see Chapter 5 for more details). Cramer (2018) focussed on the cumulative effect of the uncertainties over the whole time of production and concluded that the commercial penalty of uncertainties over a long time can be considerable. These publications suggest that allocation accuracy plays an important role in reservoir management which cannot be ignored. There is a plethora of publications that show the applications of production data in different parts of reservoir management and exploitation (Hou, Zhang and Guo 2019; Liu et al. 2019; Sadri, Mahdiyar and Mohsenipour 2019; Sun and Ayala 2019; Zheng et al. 2018). The uncertainty in the production data can also affect all these practices.

Despite the indirect and subtle effect of flow measurement and allocation uncertainty on oil and gas recovery and reservoir management, its effect on hydrocarbon accounting is direct and clear, especially where there are several owners whose wells contribute to the total commingled production. In such a case, for every single barrel of oil which is allocated incorrectly, the equivalent amount of income goes to a wrong party. The allocation calculations should therefore be undertaken as carefully as possible since the cumulative effect of any small error over time can cost the owners a huge amount of income. When considering the importance of the allocation process in hydrocarbon accounting, oil and gas companies normally have specific standards and guidelines for how to undertake it. These standards should also be in line with government regulations. The UK Energy Institute (2012) has published some guidelines for the allocation of oil and gas streams which mainly presents different methods of allocation calculations. This document has been suggested as a reference by the British Oil and Gas Authority (Guidance Notes for Petroleum Measurement 2015). The American Petroleum Institute (2011) has explained operating guidelines for allocation measurement systems in the oil and gas industry including suggestions on how to perform metering, calibration, calculations, and proving. These guidelines and recommendations can help operators to mitigate the uncertainty in obtaining production data and undertaking hydrocarbon accounting calculations. Despite the existence of these guidelines, however, there still remain considerable uncertainties in the allocation processes in some cases. One significant source of uncertainty is the lack of continuously measured production data of individual wells between two consecutive flow tests, as discussed before.

In this chapter, the effect of increasing the frequency of flow tests for individual wells on reducing the uncertainty of the allocation calculations has been investigated. In the following section, the methodology and the details of the calculations have been explained.

3.2 Methodology

The actual production data of three oil wells, measured by MPFMs, has been employed in this research (Well A, B, and C in Figure 3.4 and Table 3.1). In the first phase of the research study, the data has been used to calculate and compare the actual total production (ATP) of the wells based on the MPFM data and their estimated total production (ETP) based on occasional flow tests (Eq. 3.2 and 3.3). The error in estimations has subsequently been calculated and reported. In this phase, no allocation calculations have been undertaken since the data of a whole field is needed for such calculations. For each well, the total time of the investigation has been assumed to be the time that its production data is available and the estimated cumulative production of each well over the whole investigation time has been referred to as the estimated total production (ETP) of the well.

Table 3.1: Statistics of the well data

Well Name	Time (days)	Standard deviation (Eq. 2.7)	Relative standard deviation* (Eq. 3.5)	Arithmetic mean (STB/day)
Well A	20	105.72	0.007444695	14200.86
Well B	60	1169.55	0.060131618	17229.19
Well C	150	25104.19	0.31186466	8336.77
* The reported values for Wells B and C are the average monthly relative standard deviation. The value for Well A is based on its available production data in 20 days.				

In the oil and gas industry, the cumulative production for each time interval is considered to be equivalent to the production flow rate multiplied by the length of the production time interval (Eq. 3.1). When there are multiple time intervals, the cumulative production for the total time (i.e. ETP) is calculated based on Eq. 3.2. Production flow rate, however, is not constant over time. Therefore, assuming a constant production flow rate over a long time interval (e.g. a month) causes uncertainties in the estimated total production. The assumption is more acceptable when the time interval is shorter. In other words, choosing shorter time intervals means a more accurate ETP. ETP is theoretically in its most accurate condition when the time intervals approach zero, as shown in Eq. 3.3. Under such a condition, ETP has the same value as the Actual Total Production (ATP) which is equivalent to the area under the production flow rate plot when it is sketched as a function of time (Figure 3.2).

$$CP_{\Delta t_{i+1}} \approx Q_{t_i}(t_{i+1} - t_i) \tag{3.1}$$

$$ETP_{t_n} = \sum_{i=0}^{n-1} Q_{t_i}(t_{i+1} - t_i) = \sum_{i=0}^{n-1} Q_{t_i}\Delta t_i \approx ATP_{t_n} \tag{3.2}$$

$$ATP_{t_n} = \lim_{\Delta t_i \to 0} \sum_{i=0}^{n-1} Q_{t_i}\Delta t_i = \int_{t_0}^{t_n} Q dt \tag{3.3}$$

In Eq. 3.1 to 3.3, t is time, t_n is the total time of the investigation, $CP_{\Delta t_{i+1}}$ is the cumulative production over the $(i+1)th$ time interval, Q_{t_i} is the production flow rate at the time t_i, ETP is the estimated total production, and ATP is the actual total production. The values of all the parameters in Eq. 3.1 to 3.3 must be calculated under standard conditions in the oil and gas industry (i.e. pressure and temperature equal to 101 KPa and 288.7K, respectively) to avoid any effect of pressure or temperature change on the results of equations.

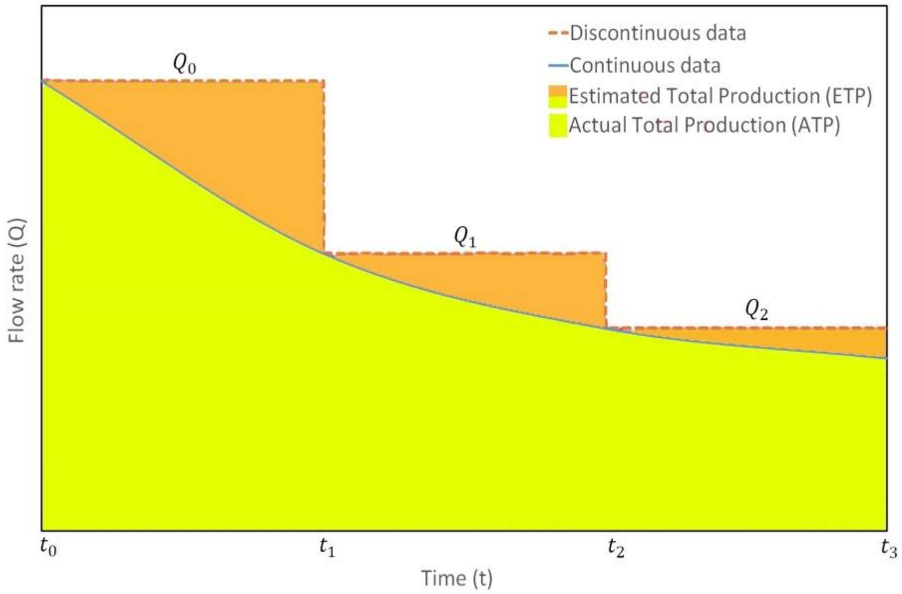

Figure 3.2: Estimated Total Production (ETP) and Actual Total Production (ATP). The area between the dashed line and the solid line shows their difference.

In practice, the time between two flow tests is the time interval in Eq. 3.2. It is the shortest time interval in which the production data for individual wells is available. Therefore, the most accurate ETP is obtained when production data for individual wells is recorded continuously, since in that case the time between two consecutive measurements approaches zero (Eq. 3.3). Although it is not always possible to obtain continuous data (e.g. installing MPFMs for each well) in practice, shortening the time interval between flow tests may be effective in decreasing ETP errors. In this research, first, the ETPs of the three aforementioned wells (Well A, B, and C) have been calculated using Eq. 3.2 for a case when one flow test per month is undertaken, that is common practice in the oil and gas industry. The results have then been compared to the respective ATPs based on the available MPFM data to determine the error in the ETPs based on Eq. 3.4:

$$E_{ETP} = \frac{ETP - ATP}{ATP} \times 100 \tag{3.4}$$

where E_{ETP} denotes the estimated total production error, ETP stands for the estimated total production (based on flow test data), and ATP is the actual total production (based on MPFM data).

In the next step, for the wells having an ETP error of over 2%, the number of flow tests per month has been increased to two, three, and four and the observed trend of decreasing the error for each well has subsequently been presented.

The ETP of individual wells is not just calculated based on the flow test measurements. In the oil and gas industry, flow test results are modified in the allocation process. Therefore, to have realistic research results, in the second phase of the research study in this chapter, the production results of a simulated oil field with 36 production wells were studied to investigate the effect of increasing the number of flow tests per month on allocation error and hydrocarbon accounting. The same fluctuations as the ones in the data sets of the three actual wells (Wells A, B, and C) were applied to the production results of the Schlumberger ECLIPSE Simulator (Schlumberger Information Systems) by employing Eq. 3.7 and using the relative standard deviation (RSD) of the real data. Therefore, three respective cases (Case A, B, and C) were created and subsequently used in the study. A relative standard deviation (RSD) (Eq. 3.5) was used instead of a standard deviation to quantify the dispersion of the data points because despite standard deviation, RSD is independent of the average production rate. In addition, the RSDs were calculated based on monthly time intervals to reduce the effect of production decline on their value. As a result, for Well B and C the reported RSDs in this work are their average monthly values. It should be mentioned that the effect of production decline over time on the value of RSDs cannot be completely eliminated since the exact trend of production decline cannot be detected in short periods of time. When the production period is short, such as a month, however, the production decline is normally small and negligible compared to the production fluctuations. Therefore, choosing short time intervals as the basis of the calculations can minimise this potential error. Combining the simulator outputs and the random numbers generated by a Matlab (The Mathworks Inc.) code based on Eq. 3.7 resulted in the reference production data for the allocation and hydrocarbon accounting calculations.

$$RSD = \frac{\sigma}{\overline{x}} \tag{3.5}$$

$$\mathbf{DF} = \frac{RSD}{\sigma_{\mathbf{RND}}}\left(\mathbf{RND} - \frac{1}{2}\right) \tag{3.6}$$

$$\mathbf{D_{ref}} = \mathbf{D_{sim}}.\left(1 + \mathbf{DF}\right) \tag{3.7}$$

In Eq. 3.5 to 3.7, σ denotes standard deviation, *n* is the number of data points, x_i represents the *i-th* data point, $\overline{x}$ is the average of all data points, **RND** denotes the vector of random numbers evenly distributed between zero and one, $\sigma_{\mathbf{RND}}$ represents the standard deviation of the vector of random numbers, *RSD* is the relative standard deviation of the actual production data, **DF** stands for the vector of dispersion factors, $\mathbf{D_{sim}}$ is the vector of the production data from the simulator, and $\mathbf{D_{ref}}$ denotes the vector of reference production data which has been used in the allocation analysis.

The allocation and hydrocarbon accounting calculations were subsequently undertaken using the Matlab code. The gap between two consecutive flow tests was considered to be a month and the length of each test was assumed to be six hours. The test flow rate for each well was considered to be the arithmetic mean of the available data points during the test time (Eq. 3.8). Allocation factors have been calculated using the test results and the accurate total flow rate of the entire field (which is equivalent to the measurements of the fiscal meters in an actual field) based on Eq. 3.9. Allocation factors which were calculated based on a flow test remained the same until the next flow test when they were updated with new values. ETP and allocation error for each well have been calculated according to Eq. 3.10 and 3.11, respectively. First, the average flow rate of each well during the test time is calculated using Eq. 3.8. The results are then used in Eq. 3.9 to determine the allocation factors for the wells. In Eq. 3.10, ETP of each well is estimated by employing its allocation factor in addition to the total production of the field. The allocation errors for the wells are subsequently calculated by Eq. 3.11.

$$\overline{Q} = \frac{\sum_{i=1}^{n} Q_i}{n} \tag{3.8}$$

$$AF_k = \frac{\overline{Q}_k}{\sum_{i=1}^{m} \overline{Q}_i} \tag{3.9}$$

$$ETP_k = AF_k.TP_{field} \tag{3.10}$$

$$AE_k\% = 100\,\frac{\sum_{k=1}^{m}\left|ETP_k^{test} - ETP_k^{ref}\right|}{2\sum_{k=1}^{m} ETP_k^{ref}} \tag{3.11}$$

In Eq. 3.8 to 3.11, $\overline{Q}$ is the average flow rate of the well during the test time, Q_i represents the *i-th* measured flow rate data point during the test, *n* denotes the total number of the available measurements of the test, AF_k stands for allocation factor for well *k*, *m* is the total number of contributing wells, ETP_k denotes the estimated total production of well k, TP_{field} is total production of the whole field (i.e. total production of all contributing sources which is measured by fiscal meters), $AE_k\%$ shows the allocation error for well k, and *test* and *ref* superscripts denote the test results and reference data, respectively.

Figure 3.3 illustrates the flow chart of the entire process of calculations undertaken by the Matlab code and the reservoir simulator. In this process, at the first step, the RSD (representing the production fluctuations) and the number of flow tests in each month for the well are given to the Matlab code as inputs. The code then generates a set of random numbers and uses them along with the production results coming from the reservoir simulator to create synthetic flow rate data with the same RSD as the inputs. Allocation calculations are then undertaken and allocation errors for the synthetic data are calculated. The generation of synthetic data and allocation calculations are repeated 100 times. The results are subsequently averaged and the cost of average errors is estimated.

The aim of the allocation process is to determine the contribution of each well to the total field production. Therefore, the allocation error in this thesis is defined as the fraction of the total field production which has been allocated to wrong wells (Eq. 3.11). Each barrel of oil which is allocated incorrectly affects the ETP of two wells: the well that truly produces it and the well that incorrectly receives it. Therefore, each single percentage of allocation error causes a two-percentage average error in the ETP of the individual wells.

The resulting errors after undertaking the calculations can properly show the uncertainty in the allocation process for the reference production data. There is no guarantee, however, that the same results are obtained for the same field and the same RSDs if the calculations are repeated with a different pattern of production flow rate fluctuations. Although an RSD shows how scattered the data is, it does not give any information about the value of the individual data points. Therefore, the reference production data can take different patterns under the same RSD which can result in different calculated allocation errors. To resolve this problem, the allocation calculations for the same RSDs were repeated 100 times and the range and arithmetic mean of the errors were obtained and reported. For each new calculation, the Matlab code generated a new set of random numbers but with the same RSD to make a new pattern in the well flow rate fluctuations. Sensitivity analysis on the number of repetitions was undertaken to make sure that 100 repetitions are enough to guarantee the reproducibility of the average results.

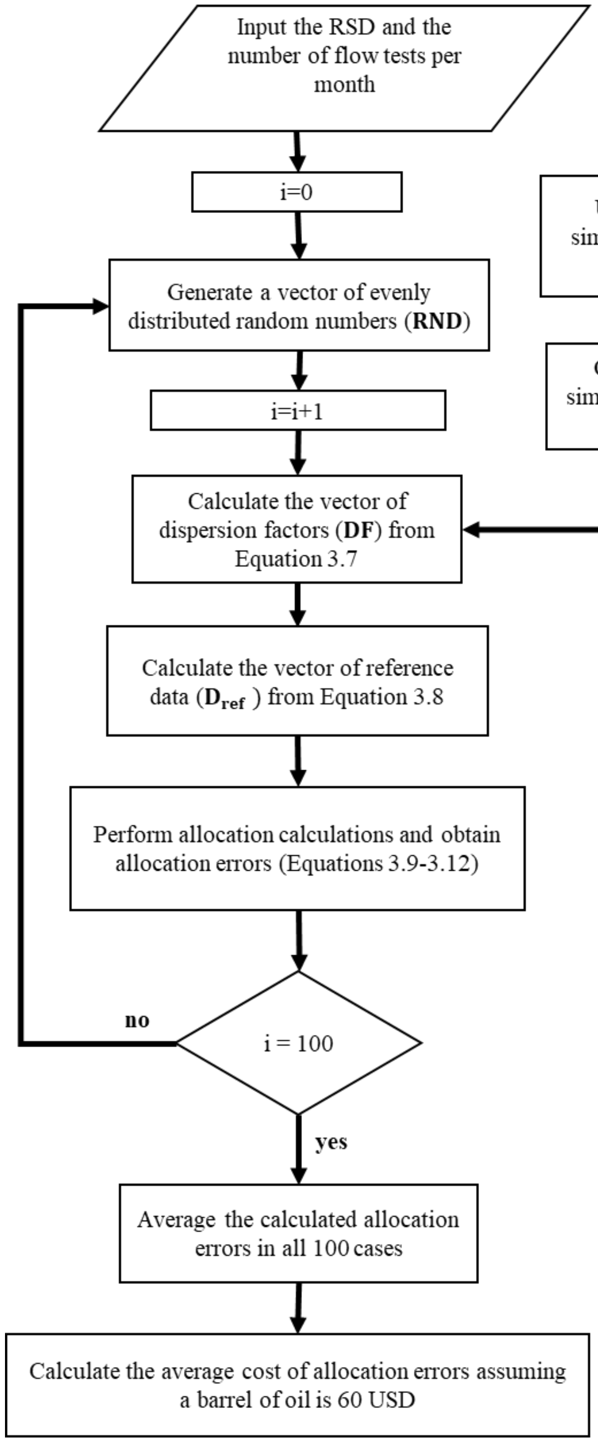

Figure 3.3: The flow chart of the process of calculations in the Matlab code and the reservoir simulator.

After undertaking the allocation calculations for one flow test per month, all the calculations were repeated for two, three, and four tests per month, respectively. The average allocation errors have been calculated and compared for all the cases. The results show how the frequency of the flow tests can affect the error in allocation calculations. For some cases, the equivalent total cost of allocation errors has also been reported (each standard barrel of oil has been considered to have a value of 60$). Finally, the change of the ETP errors of individual wells for Case C, which has had the greatest RSD, has been analysed when the number of flow tests per month has been increased from one to four. The results have been presented in the next section.

3.3 Results and discussion

As mentioned in the Methodology section, the measured flow rates data of three actual wells have been analysed in this work. The extent of the fluctuations (i.e. relative standard deviations) in these three data sets is significantly different. The ranges of fluctuations in the real data have been used to generate the ranges of fluctuations in the synthetic simulated data in this study. Figure 3.4 shows the flow data of the three actual wells (Couput 2015; Couput, Laiani and Richon 2017; Drysdale and Stockton 2015) and Table 3.1 (presented in Section 3.2) includes the values of some of their statistical parameters. The data have been measured by MPFMs and the gap between the available data points varies between 20 minutes to 18 hours.

The time interval between undertaking two flow tests with the test separator is different in different fields. Companies decide about the regularity of the tests based on different operational factors involved in the hydrocarbon production of the fields under their control. Therefore, different operators may choose to do the tests in different time intervals. It is common, however, for many companies in the oil and gas industry to test individual well flow rates at monthly intervals. One reason for this is that many companies undertake calculations related to hydrocarbon production (hydrocarbon accounting, allocation, tax payment) and prepare reports (for internal use, government authorities or publication on their websites) on a monthly basis. To investigate how accurate the results of intermittent flow tests can represent the average production of each well during the gap between two tests, the flow measurement data of the three oil wells shown in Table 3.1 was studied.

Figure 3.4 shows the oil production plots against time for Wells A, B, and C. The solid lines show the well production based on the measurements of MPFMs and the dashed lines illustrate the values of monthly flow tests. The values for the flow tests are the average of the available MPFM data points for a duration of 6 hours.

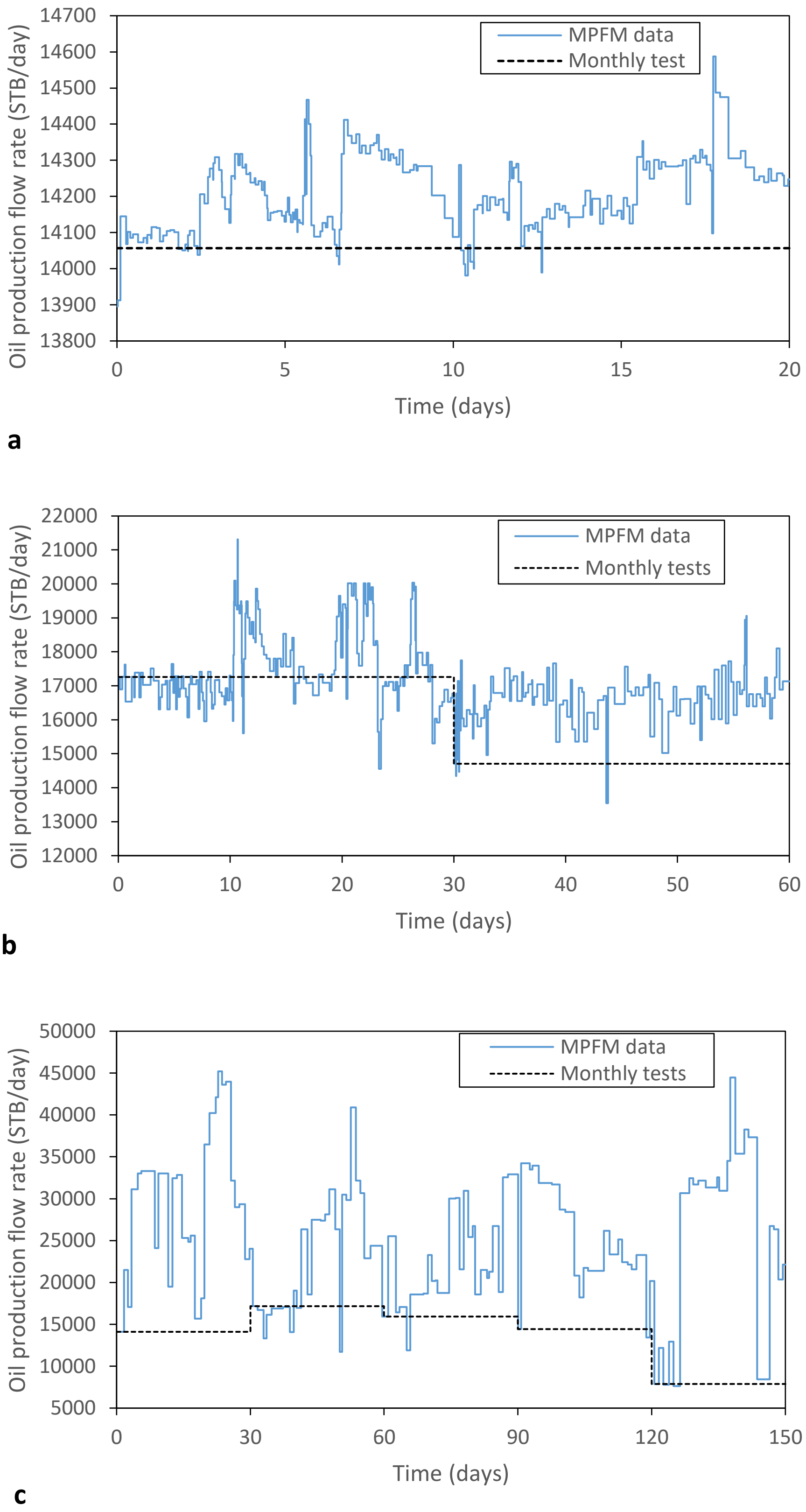

Figure 3.4: Comparison between MPFM and Flow test data for (a) Well A, (b) Well B, and (c) Well C

Figure 3.4 clearly shows the difference between the measurements of the MPFMs and the flow tests. In most time periods for the three wells, as it can be seen in Figure 3.4, the values of flow tests are smaller than the MPFM measurements. This is completely random and any other pattern can happen in other cases. The total production for each well based on the MPFM and flow test data has been calculated and compared. The results have been shown in Table 3.2.

Table 3.2: Production estimations for Wells A, B, and C

Well name	Period of production (days)	Estimated total production (ETP)				
		based on MPFM data (STB)	based on monthly flow test data (STB)	Difference (STB)	Difference ($)	ETP error (Eq. 3.4)
Well A	20	284205	281135	3070	184200	-1.08
Well B	60	1022175	958974	63201	3792060	-6.18
Well C	150	3799238	2085391	1713847	102830820	-45.11

The RSD of Well C is the largest in Table 3.1, suggesting that the measured data is scattered over a larger range compared to the other two wells. Values in Table 3.1 and 3.2 show that a greater RSD has caused an increase in the absolute value of ETP difference in the studied cases. The MPFM data has been assumed to be the actual production data of the wells since it is the most accurate data which is available in this work. The last column of Table 3.2 shows the errors in estimating the total production for the wells based on the monthly flow tests. These errors are -1%, -6%, and -45% for Wells A, B, and C, respectively, which is equivalent to 0.2M (Million), 3.8M, and 102.8M dollars’ worth of oil, respectively. The absolute values of the estimation errors for the RSDs of the three wells have been presented in Figure 3.5.

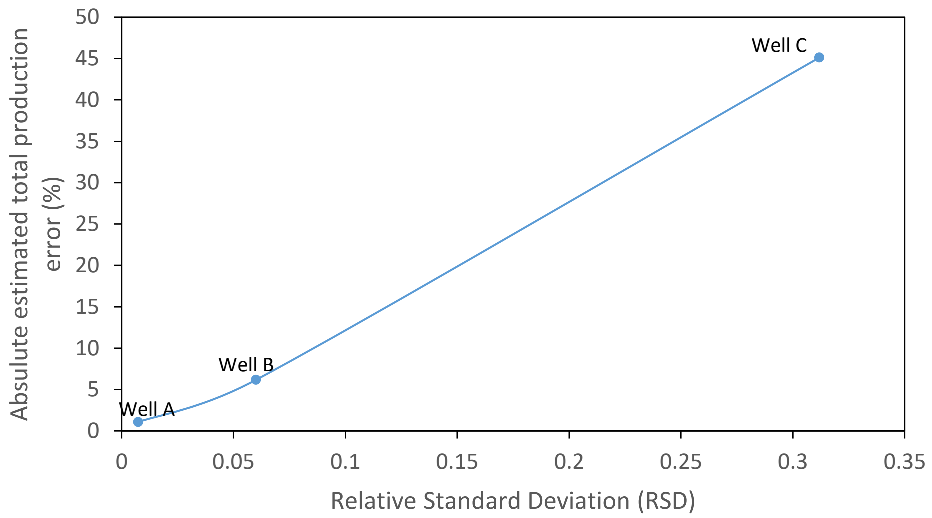

Figure 3.5: Absolute Estimated Total Production (ETP) error for Wells A, B, and C as a function of the Relative Standard Deviation (RSD) of their production data

The absolute ETP error has significantly increased when the relative standard deviation (RSD) has risen. The error goes higher than 10% when the RSD is greater than 0.08, as shown in Figure 3.5. Therefore, the results suggest that for larger RSDs in the investigated cases, estimations based on monthly flow tests include larger uncertainties. Although a general conclusion cannot be made just based on three data points, the case studies show a possibility of having large uncertainties when production fluctuations are large. It should be added, however, that in practice in the oil and gas industry, the data taken through monthly tests are combined with the measurements of the fiscal meter in allocation calculations (the details of this exercise have been explained in Section 2.4.3). Therefore, employing the data from the fiscal meter which is more accurate and regular, mitigates the uncertainty in production estimations for individual wells. The effect of the uncertainty of monthly flow test data on allocation calculations has been studied in the second phase of this research study. The results have been presented in the following lines.

The effect of increasing the number of tests per month on the absolute ETP error was investigated in order to see how the regularity of the flow tests (i.e. the time gap between two consecutive flow tests) can affect the uncertainty in the ETP of individual wells. The aim of this work was to reduce the error to less than 2%. The error for Well A based on monthly flow tests is 1.08%, as shown in Table 3.2. Therefore, the error is already within the specification.

However, for Wells B and C, the errors are greater than the target value. Figure 3.6 shows how increasing the number of flow tests per month can decrease the ETP error.

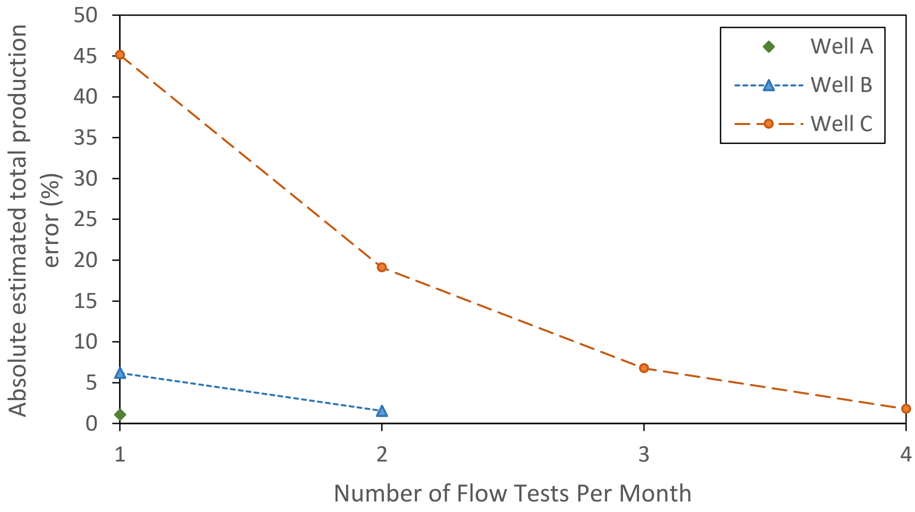

Figure 3.6: Effect of increasing the number of flow tests per month on the absolute estimated total production error for Wells A, B, and C

For Well B, however, undertaking two flow tests per month has decreased the error to less than 2%, while for Well C, with a larger RSD, four tests per month is required to achieve the same goal. It should be added that it is not always possible in practice to increase the number of flow tests per month to achieve the desired ETP error limit. What the results do show, however, is that where it is possible to regularly conduct tests, there is a reduction in the uncertainty in the estimations. Figure 3.7 shows how increasing the number of flow tests from one to four times per month can step-by-step make the estimated production plot of Well C more reflective of its production plot based on the MPFM measurements. Figure 3.7 is an example that visually shows how increasing the frequency of flow tests can make production estimations more accurate.

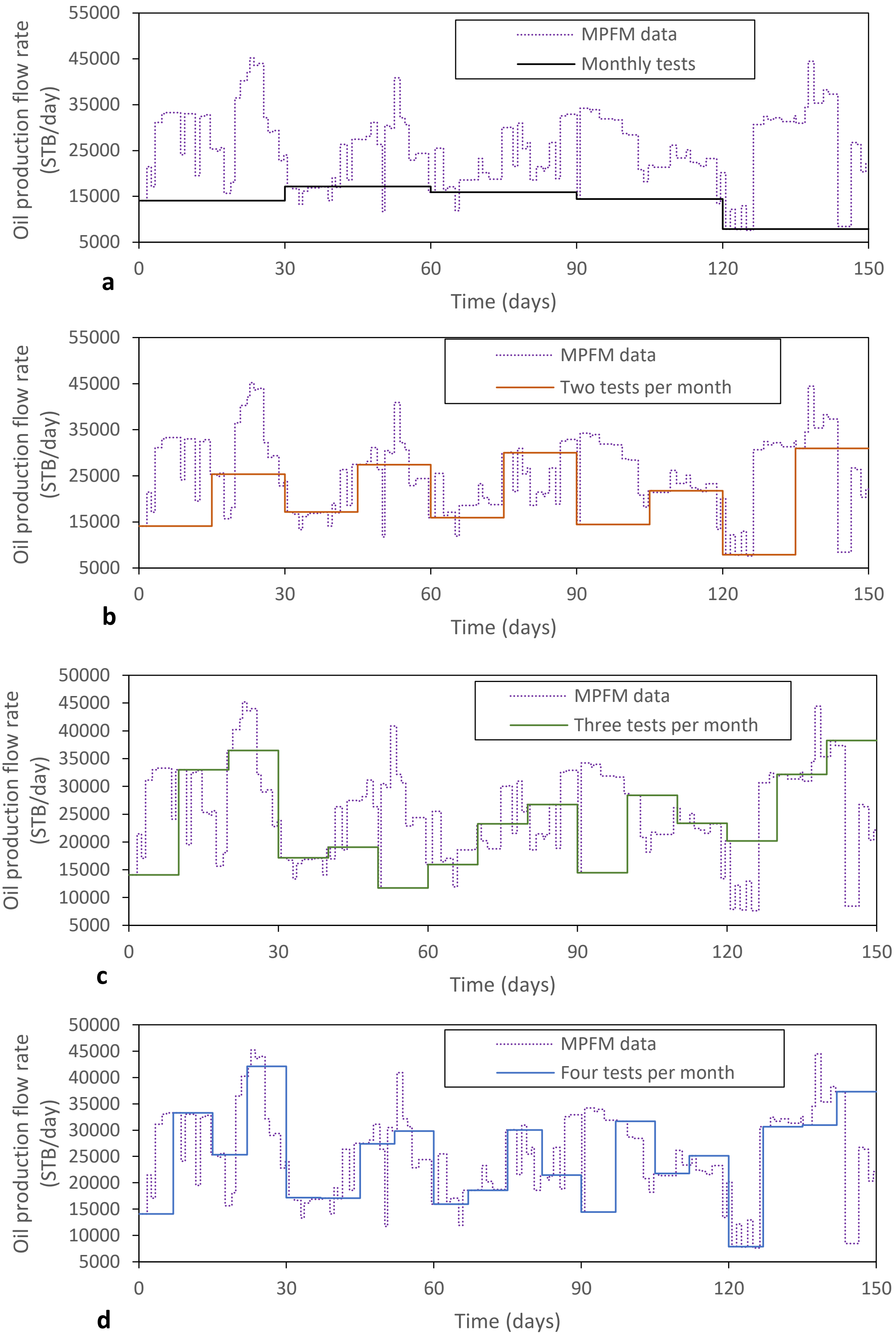

Figure 3.7: Comparison between MPFM data and flow test data when the number of flow tests per month is (a) one, (b) two, (c) three, and (d) four for Well C. When there are more flow tests per month, the test results better match the MPFM data.

As mentioned above, in the oil and gas industry, the data from the fiscal meter which continuously measures the cumulative production of several wells is employed to reduce the uncertainty in individual well production estimations. Therefore, undertaking further studies on the data of an entire field with several wells was required to see how the non-continuous scattered data of production from individual wells can affect hydrocarbon accounting.

3.3.1 Allocation calculations

An oil field with 36 production wells was simulated using the Schlumberger ECLIPSE reservoir simulator (Schlumberger Information Systems) and its production results were used to investigate the effects of uncertainties in the production data of individual wells on hydrocarbon accounting calculations in a full scale oil and gas industry case. The reservoir has been assumed to be heterogeneous in order to make it more representative. Well controls and production scenarios are set so that there is a variety in the production flow rates of different wells and their trends. The reason has been to provide enough complexity to make the hydrocarbon accounting calculations of the field similar to a real case. The simulations have been run over a year based on daily time steps which has provided enough data points for the allocation calculations. In Figure 3.8 the output of the simulator which shows the production of all wells during the year has been illustrated.

As shown in Figure 3.8, each well starts its production regime under one of the three initial flow rates (1870, 5615, or 9360 STB/day). The initial production flow rates in this scenario have been determined based on the characteristics of the drainage area of the wells. Wells which are located in more permeable areas of the reservoir start their production at a higher flow rate. Each well, however, shows a different trend of production later during the year. The characteristics of the reservoir and the wells, in addition to the constraints of production such as high water cut, have been the reasons for the later changes in the well production control. For instance, in those wells, such as Well 34, where a sudden decrease in the production has been shown, the water cut has reached 80% (their perforations are in a lower depth compared to the other wells). Therefore, the production flow rate for these wells has been decreased to reduce the total barrels of producing water from the field.

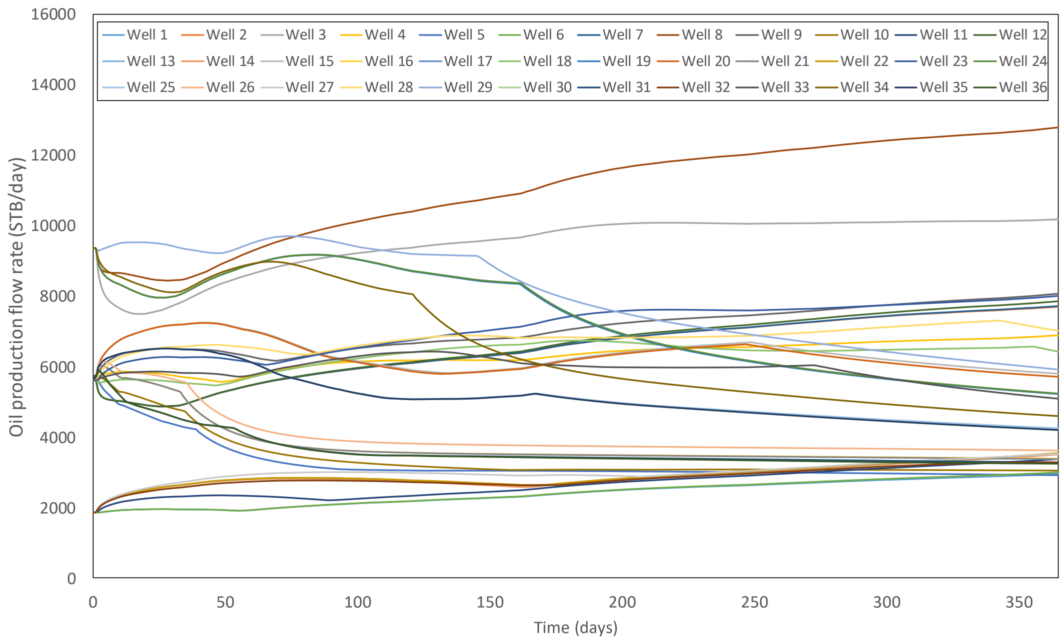

Figure 3.8: Oil production plots for all 36 wells in the simulated field

Regardless of how heterogeneous the reservoir model is made in the simulator, the actual reservoir is far more complex. There are always some fluctuations in the measured production data of the actual reservoir while the output of reservoir simulators are normally smooth, as shown in Figure 3.8. Therefore, the available production data from the actual wells which was used in the previous section (Table 3.1), was statistically analysed and the same fluctuations as the actual data were applied to the results of the simulator. In order to do that, the RSD (Eq. 3.5) of each well for each month was calculated. The average of the RSD values for each well was considered the final RSD for that well. In the next step, a Matlab (The Mathworks Inc.) code generated random numbers (positive and negative) with the same RSD as the real data and applied them to the results of the simulator. Therefore, three different sets of production data (Case A, B, and C) for the whole field with the trend of the simulator outputs and the same fluctuations (i.e. RSDs) as the real data were created for the hydrocarbon accounting analysis. As an example, Figure 3.9 compares the output of the simulator and the final production flow rate after applying the fluctuations for Well 34. It should be noted that using real data for production in a research undertaking is ideal. It is difficult, however, to find the production data of an entire field where the production flow rate of all wells is measured by MPFMs or in daily intervals (if such data exists at all). In addition, the simulator can provide an unlimited number of data sets which is necessary for securing the repeatability of the research results. This clearly could not happen with the limited number of real data sets if they were available. As a result, in this research the limited available actual data for three individual wells were combined with the outputs of the reservoir simulator (Schlumberger ECLIPSE) to benefit from the advantages of performing an unlimited number of simulations and make the case similar to a real case in the oil and gas industry.

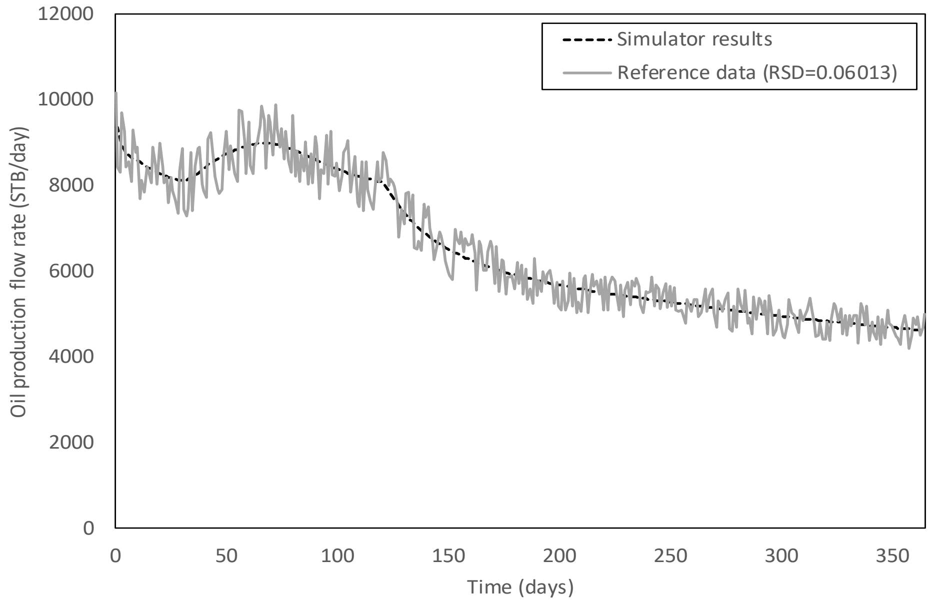

Figure 3.9: An example of the reference data generated by combining the simulation results for Well 34 and the real data of Well B. Simulator output plots are smooth while real production data is dispersed.

After adding the fluctuations to the production outputs of the simulator, the resulting data set was employed as the reference data set in the hydrocarbon accounting calculations. This implies that we assumed that the resulting data set was equivalent to the measured production data of the field. The same approach as the one explained in the previous section was employed to extract monthly flow test data for the individual wells. Allocation based on combining accurate measurements of the fiscal meter and the data from intermittent well flow tests is the main part of hydrocarbon accounting calculations. Therefore, in the next step, the flow test data and the total flow rate of the field (which is equivalent to the data of the fiscal meter) were input to a Matlab code. The code was prepared to undertake allocation calculations based on the methods and equations presented previously in the methodology section and the flow chart in Figure 3.3. The results of allocation calculations were subsequently used in the hydrocarbon accounting and compared with the calculation results based on the reference data to investigate the extent of errors caused by the uncertainty in the intermittent individual well flow data. Since fluctuations have different distribution patterns in different production data, it might not be accurate to generalise the research results based on one or a few study cases. Therefore, the entire process explained earlier, was repeated 100 times. Since the Matlab code generates new random numbers each time, the pattern of fluctuations in the production data is different from the previous times. As a result, for each case, 100 production data sets have been analysed. In addition to the three RSDs from the actual wells, similar calculations have been undertaken for six more RSDs (0, 0.05, 0.1, 0.2, 0.3, and 0.4). The results of all the calculations have been summarised in the shape of the box and whisker plot in Figure 3.10.

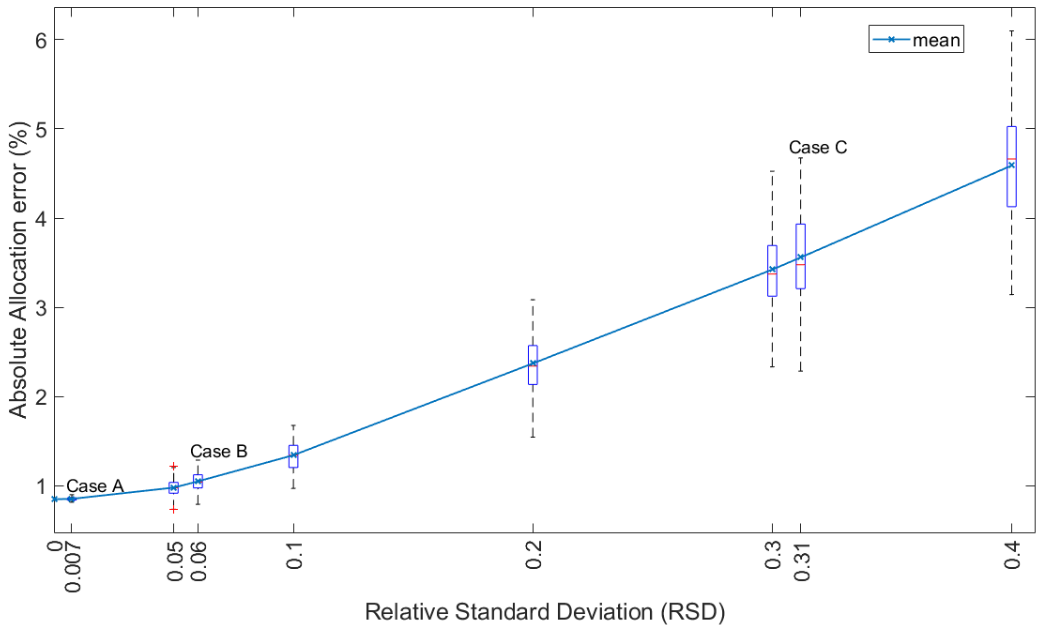

Figure 3.10: Box and whisker plot of absolute allocation errors as a function of relative standard deviations of Cases A, B, and C and six more arbitrary RSDs.

Figure 3.10 shows the average and the distribution of errors in allocating total production to wells in 300 times calculations which have been undertaken for the three cases (100 times per case). The same calculations have been performed for six other boxes in the plot. The six arbitrary boxes have been added to the graph to extend the RSD range and have enough RSDs to make sure the plot shows a correct trend. The solid line in the graph shows how the mean of the absolute allocation errors changes against the RSDs. Moreover, the boxes and whiskers show the range of errors and their median and upper and lower quartiles for each RSD. The error has been calculated based on the method explained in the methodology section (Eq. 3.11) and shows the percentage of the total production of the field which has been allocated to a wrong well. Both the average and the range of the error increase with a greater RSD. The average error was 0.85% for Case A (RSD=0.0074), while it has risen to 1.05% for Case B (RSD=0.0601) and 3.58% for Case C (RSD=0.3119). The range of error has also increased from Case A to Case C. The largest errors were 0.90%, 1.29%, and 4.67% for Cases A, B, and C, respectively. Figure 3.10 shows the error for the entire field. The error for an individual well, however, is different from the error for the entire field-being twice the error of the entire field. Note that each barrel of oil which is allocated to a wrong well is counted once for the entire field so it affects two individual wells: one well loses the barrel of oil in the estimations and the same barrel of oil is allocated to another well. Therefore, it increases the error of both wells (for one of them in the positive and the other one in the negative direction) and hence makes the average absolute error of all wells double the size of the field error. Performing allocation calculations for the individual wells also approves it. The calculated average absolute errors for the individual wells were 1.7%, 2.10%, and 7.16% for Cases A, B, and C, respectively. Figure 3.11 shows the average absolute errors of all individual wells for each case.

Comparing the results in Figure 3.5 (flow test errors) and Figure 3.11 (allocation errors) shows how allocation calculations can affect the errors in the estimated production of wells. The absolute errors for actual Wells A, B and C (Figure 3.5) were 1.08%, 6.18%, and 45.11%, respectively. The average absolute results for Case A (1.7%) is more than the error for Well A (1.08%). The reason is that the available data of Well A is for just 20 days and its production trend has not changed significantly while the allocation error is based on one year production, including ups and downs in the well production trends. For the other two wells (B and C), the allocation errors of their respective cases (B and C) are significantly smaller than the flow test errors, although the RSDs are the same.

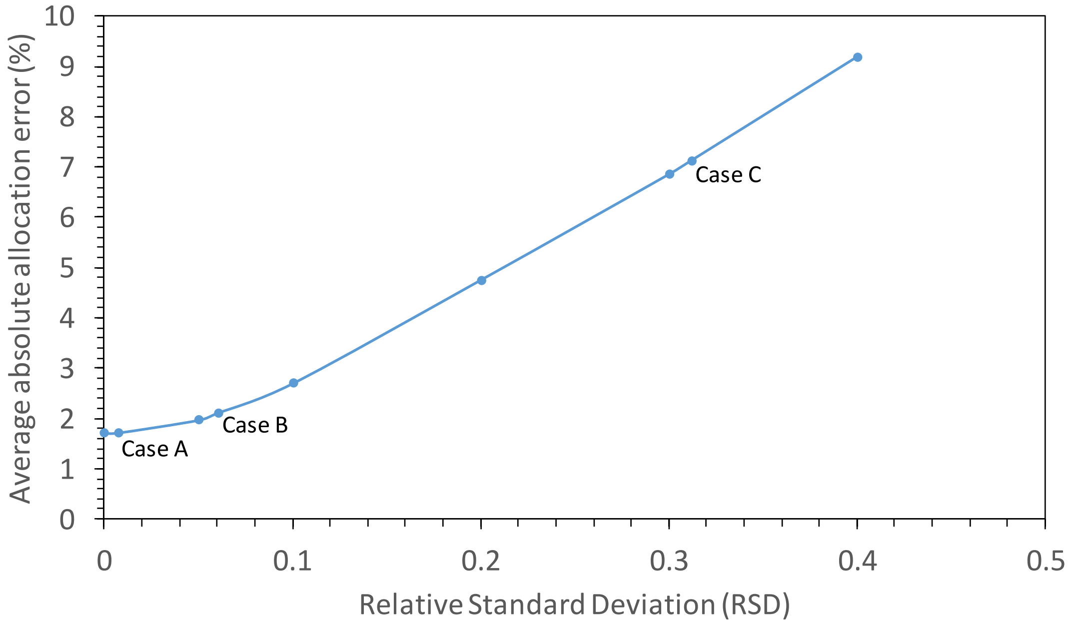

Figure 3.11: Absolute average allocation error for all individual wells in each case. The average absolute error for individual wells is twice as the average absolute error for the entire field.

Although employing allocation techniques and using more accurate data of the fiscal meter, in addition to less accurate data of flow tests, can mitigate the uncertainty in the results, the errors for some cases are still unacceptable in terms of hydrocarbon accounting. The average total amount of produced oil during the year which has been allocated to a wrong well and its equivalent price (assuming the value of each barrel is 60 US dollars) has been reported in Table 3.3.

Table 3.3: Hydrocarbon accounting calculation results including the total cost of wrong allocations for one flow test per month

Case	Period of production (days)	Average total oil production (STB)	Average total oil allocated to wrong wells (STB)	Total cost of wrong allocation (US$)	Percentage of the total production (allocation error)
Case A	365	70,396,118	598,367	35,902,013	0.85%
Case B	365	70,069,333	735,728	44,143,661	1.05%
Case C	365	69,625,196	2,492,582	149,554,906	3.58%

As shown in Table 3.3, allocation error shown in the last column might not look significant in some cases but its cumulative effect over a long time has a significant financial impact on the operator companies. In cases where different companies own different wells in the same field or the production from the wells of one company is commingled with the production of other companies for any reason, these costs can cause the companies to lose a large amount of income over a long time due to the allocation errors. The errors can also affect tax calculations or reservoir management (Chen and Xu 2019; Cramer 2018; Marshall et al. 2019; Sadri, Shariatipour and Hunt 2017; Sadri et al. 2019). Table 3.3 shows that the total costs for Cases A, B, and C are 35.9M (Million), 44M, and 149.5M dollars during a year of production. These numbers show the price of the total amount of produced oil that has been allocated to wrong wells. If we assume every single one of the 36 wells in this field has a separate owner, it means the reported cost is the sum of the money which has gone to wrong owners. Under such an assumption in Case C, some owners lose 149.5 million dollars of the total value of their yearly production while the rest of the owners receive the same amount of money more than the value of the oil that they have produced. Table 3.3 clearly shows that the allocation errors can cause owners to lose large amounts of their income over time, especially when the RSD of the production data is high (i.e. the production rate has large fluctuations and the recorded production data is highly scattered) such as in Case C. As a result, reducing allocation errors can have significant benefits for the companies in the oil and gas industry. The results that have been presented here are for the studied case. In oil and gas fields, the same analysis can be undertaken by calculating RSDs obtained from flow test results.

Previously, it was shown that by performing more frequent flow tests, the errors in the estimated total production (ETP) of individual wells can be reduced. In this section, the effect of increasing the frequency of flow tests on allocation error has been presented. In order to obtain the following results, the number of flow tests per month was increased from 1 to 2, to 3, and then to 4 and its effect on the accuracy of allocation results for all three cases was investigated. As before, all calculations have been repeated 100 times with different input random data sets and then the results have been averaged to make sure that the final results are reproducible. The allocation error as a function of the number of flow tests per month has been shown for Case A, B, and C in Figure 3.12.

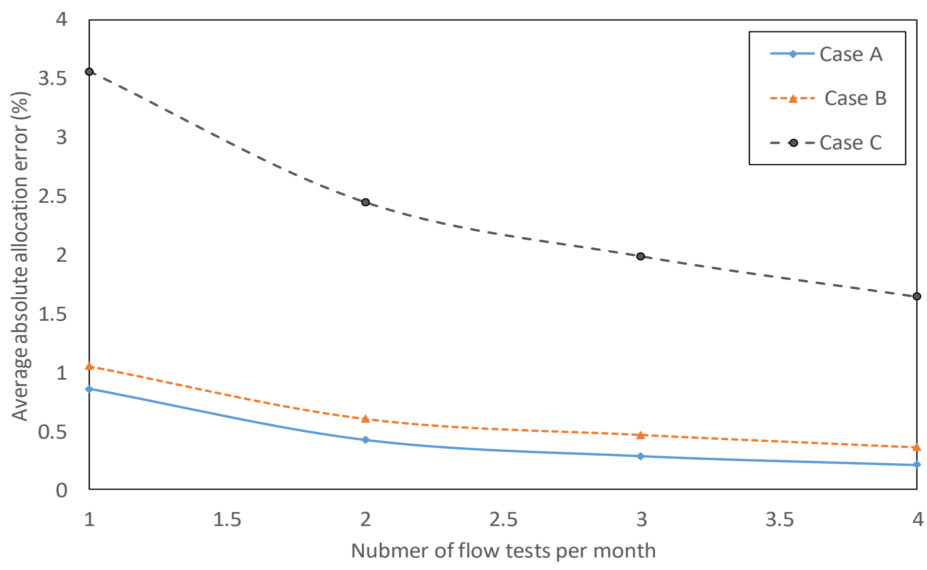

Figure 3.12: Average absolute allocation error as a function of the number of flow tests per month. Undertaking more flow tests per month has decreased allocation uncertainty in all cases.

Increasing the number flow tests per month decreased the allocation error in all three cases, as illustrated in Figure 3.12. In all cases there is a sharper decrease from one test per month to two, then it continues with a smoother slope to three and four tests per month. Increasing the number of flow tests per month from one to two decreased the allocation errors of Cases A, B, and C by 0.43%, 0.45%, and 1.11%, respectively, which are equivalent to 18.2M, 18.9M, and 46.8M US dollars reduction in the yearly cost of allocation error for the respective cases. Table 3.4 shows how increasing the number of the tests per month (TPM) can reduce the cost of allocation error for all cases.

Table 3.4: Reduction in the total yearly cost of allocation error when increasing the number of flow tests per month

Case	Reduction in the total yearly cost of allocation error when increasing the number of flow tests per month (million dollars)		
	1TPM to 2TPMs	1TPM to 3TPMs	1TPM to 4TPMs
Case A	18.2	24.0	27.1
Case B	18.9	24.5	29.0
Case C	46.5	65.7	80.1

Based on Table 3.4, the results show that undertaking more flow tests per month can reduce the total cost of allocation. In practice, however, there are many other factors which should be considered. Firstly, performing more frequent tests may not always be possible due to operational constraints. Secondly, more flow tests require more operational or even capital expenditure. Therefore, the constraints need to be considered and the costs and benefits be estimated and compared for each individual field. Another option is installing MPFMs for individual wells. MPFMs can provide real-time continuous production data for individual wells. Some MPFM manufacturers and experts also believe that, as there is no need for test separators when MPFMs are installed on wells, therefore they can eliminate the capital cost spent on installing the test separator and its related flow lines. Installing MPFMs, however, also requires spending on capital and operating costs. The price of MPFMs and the cost of their maintenance should also be considered. The well which is equipped with the flow meter might also need to be shut for the duration of the installation of the hardware if the MPFM is intrusive. All these aforementioned factors create extra costs which should be compared with the benefits before making any decision. Another fact that needs to be regarded is that the benefit to all owners from increasing the accuracy of the measurements is not the same. Although the average cost for the entire field is reduced, some owners might benefit more than the others. To show how more frequent tests can affect each single well, allocation calculations for Case C were performed using the same random number data set (i.e. exactly the same fluctuations in the production flow rates) for when 1, 2, 3, and 4 flow tests per month are performed. Figure 3.13 illustrates the allocation errors for all 36 individual wells and also the average absolute allocation errors for all wells.

Although the average error decreased with more flow tests per month, the same trend is not seen for all individual wells. This is because of the random pattern of the fluctuations in well productions and the random nature of allocation calculations. While for Wells 10, 31, and 36 a decreasing trend in the absolute value of the errors is seen, the rest of the wells have a random trend. Well 22 has had the largest error of all for one test per month (TPM) which has been 22.92%. It has gone down to -0.91% for four TPMs. The largest negative errors are those for Wells 26 and then 17 with -15.94% and -15.46%, respectively, associated with one TPM. It can potentially mean over 15% of the value of their yearly production does not go to their owner but to the owners of other wells.

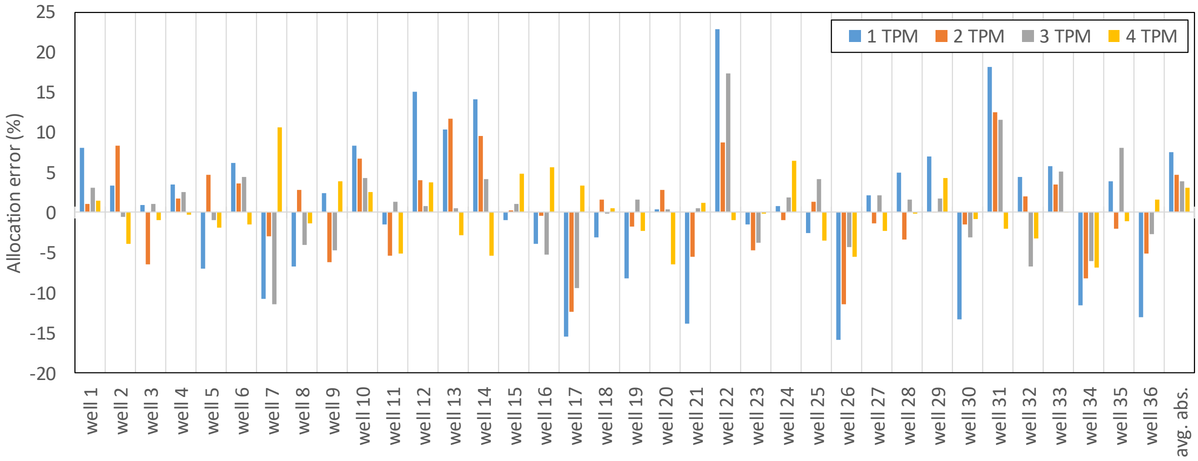

Figure 3.13: The change of allocation errors for individual wells in Case C when the number of tests per month is increased. Avg. abs. denotes average absolute error of all wells.

For one TPM, there are seven wells which have negative errors larger than -10%. There are just two wells that have the same condition for two TPMs. For three TPMs and four TPMs it decreases to one and zero wells, respectively. Therefore, the allocation is 'fairer' when there are more TPMs as it is also approved by the average values in Figure 3.13. Figure 3.13 also shows the largest errors occur under a different number of TPMs. Despite the falling trend, the largest error increased from two TPMs to three TPMs. When many cases are analysed, however, the overall trend is expected to fall. Therefore, the above exercise was repeated 100 times with different sets of random numbers (i.e. different well production rate fluctuations) to examine it. The results approve the expectation as shown in Figure 3.14.

Figure 3.14 suggests that performing more flow tests on individual wells not only is important in hydrocarbon accounting, but can also be effective on reservoir management. Although the average absolute error of all wells for one TPM might be negligible (7.16%) in reservoir management compared to other large uncertainties in a reservoir, the errors of individual wells that can go up to 35% cannot be ignored. Therefore, decreasing the maximum error for individual wells through performing more frequent flow tests can play a role in having improved reservoir management and increase the oil and gas recovery. The best results in theory, however, are achieved when each individual well is equipped with an MPFM which can provide accurate continuous real-time data.

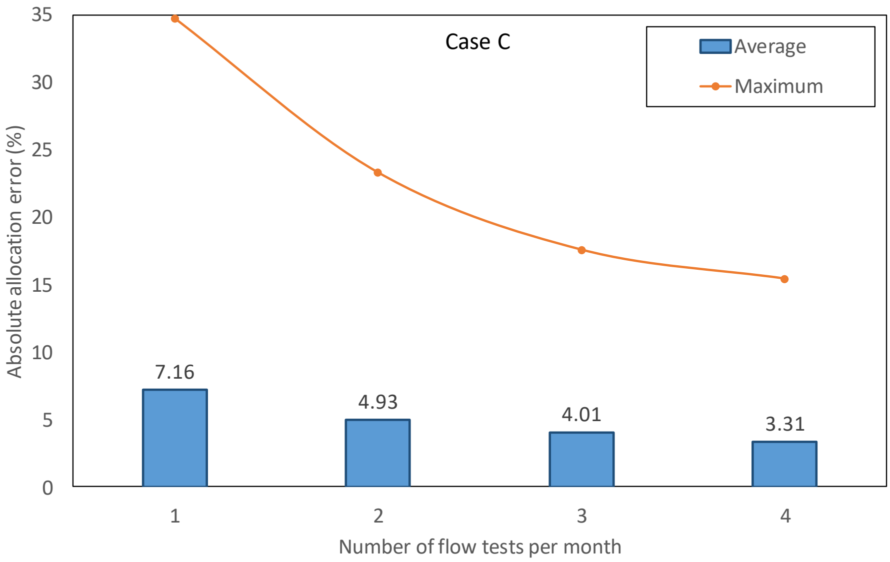

Figure 3.14: Maximum and average absolute allocation errors of individual wells in 100 allocation calculations for Case C when one to four flow tests per month are undertaken. The trends of both average and maximum errors are falling.

3.4 Conclusions

In this chapter, the effect of the frequency of performing flow tests for individual wells on their Estimated Total Production (ETP), allocation errors, and hydrocarbon accounting for the entire field was studied. The near-continuous real production flow rate data of three actual wells was employed to investigate how increasing the number of flow tests per month (TPM) can reduce the uncertainty in estimating total production of each well. Results showed that for wells with largely dispersed production data (i.e. flow rates with large fluctuations), there is a larger error in ETP. Increasing the number of TPMs, however, can significantly reduce ETP errors. For the well with the largest data dispersion in this research, the ETP error was reduced from 45% to less than 2% when the number of TPMs was increased from one to four.

In order to investigate the effect of the number of TPMs on allocation errors and hydrocarbon accounting, the production data of a simulated oil field with 36 production wells was analysed. The same data dispersion as the three actual wells was applied to the simulator outputs using the relative standard deviation of the actual data to make three cases similar to the real situations. Allocation and hydrocarbon accounting calculations for one, two, three, and four TPMs were subsequently undertaken for all the cases using a Matlab code. All calculations were repeated 100 times to secure reproducibility of the results and to provide the opportunity for statistical analysis. The results show larger average allocation errors and also wider ranges of error for higher RSDs. The average allocation errors were 0.85%, 1.05%, and 3.58% for RSDs equal to 0.007, 0.060, and 0.312, respectively, when there was only one TPM. These errors lead to $36M (Million), $44M, and $150M total yearly cost for the whole field for the respective cases. The results show that increasing the number of TPMs from one to four can reduce the allocation errors to 0.21%, 0.36%, and 1.64% which are respectively equivalent to $27.1M, $29.0M, and $80.1M reduction in the total yearly allocation cost for the entire field.

There can be operational constraints and capital and operating costs involved in undertaking more frequent flow tests in some fields. Moreover, as the analysis of the errors for individual wells has shown, all owners who have a share of the total production might not benefit equally from more TPMs. However, the results show that when there are more TPMs, the total cost for the entire field is reduced, hydrocarbon accounting calculations are more accurate, there is a fairer allocation of the total production to individual well owners, and there is less uncertainty in the production data used in reservoir management.

Chapter 4: Application of an artificial neural network for mitigating allocation uncertainties†

In many oil and gas fields, the production data of individual wells is estimated by undertaking occasional flow tests and through an allocation process. There are, however, large uncertainties associated with the obtained production data that can subsequently affect hydrocarbon accounting and reservoir management. As discussed in Chapter 3, increasing the regularity of flow tests can reduce the uncertainty, but it also incorporates extra costs. Finding the minimum number of flow tests required to reduce the error of the data to less than a desired value is therefore of vital importance. In this chapter, a machine learning technique has been employed to achieve this aim. An artificial neural network (ANN) has been trained to find the relationship between the statistical characteristics of the production data of oil wells and the minimum number of flow tests a month required for each well to secure an estimate of the production data within a target error specification. Employing this method can help to minimise the cost of increasing the number of flow tests at the same time as securing a desirable accuracy for the obtained production data.

† The contents of this chapter have been extracted from the following paper:

Sadri, M. and Shariatipour, S. (under revision) 'Employing an artificial neural network to reduce the uncertainty in oil and gas production data '. Journal of Energy Resources Technology.

The candidate developed the methodology, undertook the required simulations, wrote the Matlab codes, analysed the results, and prepared the article. Seyed M. Shariatipour supervised the research.

4.1 Introduction

Oil and gas production data is largely used in different exercises in the oil and gas industry, such as for hydrocarbon accounting (Chen and Xu 2019; Cramer, Schotanus and Colbeck 2009; Cramer et al. 2011; Ikiensikimama and Ajienka 2012), production engineering (Azamipour et al. 2017; Sadri, Mahdiyar and Mohsenipour 2019; Sun and Ayala 2019), and reservoir management (Marshall et al. 2019; Sadri, Shariatipour and Hunt 2017; Sadri et al. 2019; Zheng et al. 2018). The calculations, simulations, and forecasts in these exercises and the decisions made for the hydrocarbon field can, therefore, be affected by any uncertainties in the production data. As a result, these uncertainties can create additional costs for operators, or reduce hydrocarbon recovery from reservoirs. The cost of these uncertainties can be significant in hydrocarbon accounting (Cramer et al. 2011; Sadri and Shariatipour 2019) and reservoir management (Marshall et al. 2019; Sadri et al. 2019).

Although the application of multi-phase flow meters (MPFM) in the oil and gas industry has recently increased (Falcone, Hewitt and Alimonti 2009; Falcone et al. 2002; Theuveny and Mehdizadeh 2002), there still remains many hydrocarbon fields in which the flow rates of production wells are only estimated using allocation methods. In such fields, the production streams from different wells are mixed without their flow rates being measured individually. The total flow of all wells is subsequently sent to the separation unit and the single-phase flows of oil, gas, and sometimes water, are measured by flow meters. Therefore, the only continuous production data which is available is the data of the total production of all the wells. The flow rates of individual wells, on the other hand, are only measured during a short occasional exercise which is called a ‘flow test’, ‘well test’, or ‘daily test’. During a flow test, the production of an individual well is sent to a ‘test separator’ for a short time (the test time can be as short as an hour or as long as a full day) before it is commingled with the total production flow. The phase flow rates of the well are therefore measured during the test time. The results of the test are used to calculate ‘allocation factors’ that determine the contribution of each well to the total production (Energy Institute 2012). These allocation factors, in addition to the total flow rate measurements, are employed to estimate the production flow rates of individual wells when no flow test is performed. Flow tests are normally repeated in certain time intervals to update allocation factors. The time intervals can vary between a few days to a few months based on well characteristics, technical and financial considerations, and the difficulty of accessing a well.

Although the process of allocation provides an estimation of production flow rates for individual wells, there remains a large uncertainty in the obtained production data. Flow rates of production wells do not remain constant over the timespan between two consecutive flow tests and, in addition, there are normally natural fluctuations in the production flow rates. There are also other perturbations, such as water or gas breakthrough, during the time between two flow tests that can dramatically diverge the production flow rate of the well from what it was at the time of the flow test. As a result, there are normally large errors in the production data obtained through an allocation process as it was discussed in Chapter 3. Considering the potential costs that these errors can cause, some oil and gas companies are trying to find solutions to improve the accuracy of the data. One solution is installing MPFMs on individual wells, which requires large capital and operating costs. Moreover, if the MPFMs are intrusive, the wells need to be shut during the installation phase, adding considerably to the costs of the operation. Therefore, finding alternative methods that can improve the accuracy of the production data of individual wells can play an important role in reducing the cost of production. A number of researchers, therefore, have undertaken studies to mitigate allocation uncertainties. Cramer et al. (2011) reported using a data-driven modelling application in the allocation process. They recommended that performing a daily allocation through their approach provides more accurate production data than traditional allocation methods based on periodic well flow tests. Stockton and Allan (2012) described potential pitfalls in analytical allocation uncertainty calculations and provided recommendations on how to avoid them. They used a stochastic Monte Carlo approach in addition to the typical analytical calculations and concluded that the approach can improve calculating uncertainties. Kaiser (2014) compared the production rates of individual wells estimated based on decline curves and allocation techniques. The author concluded that although a more accurate estimated ultimate recovery and a better understanding of individual well behaviour can be obtained through the decline curve method, it incorporates more calculations. Pobitzer, Skålvik and Bjørk (2016) employed a cost-benefit approach to optimise metering uncertainty in allocation setups. Their algorithm helps finding a proper meter and locate it in its right place for a more accurate allocation process. Acuna (2016) used real-time virtual flow metering by employing pressure and temperature data in a case study. The author reported that the allocation errors of the studied field were reduced to less than 10% by employing the promoted method.

In Chapter 3, we showed that increasing the regularity of flow tests can improve the accuracy of production data significantly. Undertaking more flow tests, however, necessitates a higher operational cost and in some cases, it incorporates technical difficulties. A good example of the latter case is where wells are located in remote and difficult to access areas. One way to undertake the occasional flow tests on these types of well is to employ portable multi-phase flow meters (MPFM) installed on trucks. There are normally no facilities around these wells, making the operation practically difficult and financially expensive. Therefore, an optimisation procedure is needed to secure an acceptable production data accuracy required for hydrocarbon accounting and reservoir management for a minimum number of flow tests.

The frequency of flow tests is typically decided by operators based on the circumstances they face in the field, such as the stability of production rates. Performing one test each month is common in many oil fields since it is consistent with monthly report formats and calculations (e.g. hydrocarbon accounting, tax payment) in the oil and gas industry. If the accuracy of the data of individual wells is important, for instance where there are several owners whose wells contribute in the total production, however, the tests might be undertaken more regularly. Another example of a situation in which more regular tests are needed is where well production rates are unstable or have large fluctuations.

As a general rule, when the frequency of the flow tests is increased, the possibility of achieving more accurate production data increases (Sadri and Shariatipour 2019). There still remains one question, however, about the exact number of flow tests per month needed to be taken which can guarantee a reduction in the well data errors to less than a desired error specification. For instance, if the desired error specification for a well is 4%, the question is with how many flow tests per month on that well its estimated production rates (obtained by allocation calculations) will have errors within the range of -4% to +4%. Although at present, finding a completely correct answer to this question looks difficult, the aim of this chapter is to suggest a machine learning technique that can provide acceptable and helpful responses for certain ranges of error specifications.

The application of machine learning or specifically Artificial Neural Network (ANN) in virtual flow metering has been addressed in some research projects before (Ahmadi et al. 2013; AL-Qutami et al. 2018). There is, however, a dearth of publications in the literature about the application of these techniques in an allocation process. Shoeibi Omrani et al. (2018) employed a machine learning approach to increase the accuracy of both virtual flow metering and allocation results for individual wells. The inputs of their ANN were the choke opening, the number of wells, the pressure, and temperature. They, therefore, used a data-driven virtual flow metering model to improve the accuracy of the estimated flow rates of individual wells. Their model, however, does not analyse or consider the fluctuations in the production flow rates directly and it also does not provide any outputs about the required regularity of flow tests for wells in the field.

The research presented in Chapter 4 has focused on improving the accuracy of the allocation process itself and not through virtual flow metering. The effect of production fluctuations, which is one of the main sources of allocation uncertainty, has been analysed and considered in this research. In this chapter, an ANN algorithm has been employed to find the minimum number of flow tests per month (TPM) that should be performed to guarantee that allocation errors remain below a certain error specification. The details of the methodology and the results have been presented below.

4.2 Methodology

Fluctuations in continuous production data (measured by MPFMs or test separators) of seven actual wells have been statistically analysed in this work. These fluctuations are important since they change the actual production flow rates over time and cause the average flow rate estimations based on allocation calculations to be different from the real well flow rates. The range, magnitude, and distribution of fluctuations in the real data have been quantified using the standard deviation (Eq. 2.7), mean (Eq. 2.6), skewness (Eq.4.1), and kurtosis (Eq. 4.2) of the data sets. These four parameters were chosen for the quantification because they are well-known parameters in statistics that can properly represent the average and the distribution of the data.

$$s = \frac{\sum_{i=1}^{n}\left(Q_i - \overline{Q}\right)^3}{n\,\sigma^3} \tag{4.1}$$

$$k = \frac{\sum_{i=1}^{n}\left(Q_i - \overline{Q}\right)^4}{n\,\sigma^4} \tag{4.2}$$

where σ stands for the standard deviation, n is the number of production flow rate data points which are available, Q_i denotes the *i-th* data point, $\overline{Q}$ is the average production flow rate, s stands for skewness, and k represents kurtosis.

Based on the calculations, the ranges of all four aforementioned parameters were obtained for the actual wells.

The value of these four parameters have later been used as the inputs of the neural network. Training the neural network only with the available real data sets was, however, not possible. The reason is that, in order to train a neural network, the outputs (network targets) must also be known, as well as the inputs. For real cases, however, the targets (i.e. the exact minimum number of flow tests per month that must be undertaken to reduce the error to less than a certain specification) were unknown. Therefore, employing a reservoir model (i.e. reservoir simulator) was necessary to calculate the targets (outputs) corresponding to the inputs. Therefore, the production results of a simulated oil field with 36 oil wells were used to perform allocation calculations and calculate the network targets. The length of production for all wells was set to be one year.

The results of a reservoir simulator can show the trend of production and its changes over time. Since there is always more complexity and heterogeneity in an actual reservoir compared to a reservoir model, however, the same fluctuations seen in actual data are normally not seen in simulation results. Therefore, to make the flow rates as similar as possible to the real production data, similar fluctuations were added to the simulator (Schlumberger ECLIPSE (Schlumberger Information Systems)) results based on the ranges of the four statistical parameters (mean, standard deviation, skewness, and kurtosis) previously calculated for the seven actual wells. In order to make sure that the magnitude and distribution of the implemented fluctuations cover all the ranges possible to occur during actual production, 10000 random numbers within the calculated ranges of the statistical parameters were generated for each parameter by a Matlab (The Mathworks Inc.) code. Mean and standard deviation were combined in one parameter, which is called the Relative Standard Deviation (RSD). RSD is defined as the standard deviation (σ) divided by the mean ($\overline{Q}$) as shown in Eq. 3.5.

The ranges for the parameters (RSD, skewness, and kurtosis) are shown in Table 4.1. As a result of implementing all 10000 sets of the three random numbers to the production flow rates of the 36 simulated wells, 360000 different realisations with different well production patterns were obtained. These realisations were later used in allocation calculations and subsequently in training and validating the neural network.

Table 4.1: Range of values of statistical parameters in all realisations

Parameter	Minimum value	Maximum value
Relative standard deviation	0	0.5
Skewness	-1	1
Kurtosis	1	5

An artificial neural network (or generally any machine learning technique) needs a set of targets for its training. After obtaining the realisations by combining the actual data and the results of the reservoir simulator, the allocation errors of each realisation need to be calculated to enable them to be used as the targets of the ANN. Therefore, a piece of the Matlab code undertook allocation calculations based on one, two, three, and four flow tests per month, respectively. The details of allocation calculations have been presented in Chapter 3 and by Sadri and Shariatipour (2019). It was assumed that each test flow rate was equal to the average flow rate of the well during the test time. The duration of each test was six hours. Allocation errors for each realisation were therefore calculated as a function of the number of flow tests per month. The Matlab code, in the next step, was used to find the minimum number of TPMs needed to reduce the allocation error for each realisation to less than the determined error specification. The Matlab code also flagged those realisations in which undertaking up to four TPMs could not reduce their allocation error to less than the error specification. For these flagged realisations, 'more than four TPMs' are needed to meet the error specification. The process was repeated for different error specifications and for each error specification the matrix of targets was calculated and stored for the later use in the neural network.

The Neural Network Toolbox (Hudson Beale, Hagan and Demuth R2017a) of Matlab was trained in the last stage of this research to find the relationship between the inputs and targets. An ANN was chosen to be used in this work because it is more versatile compared to other methods such as a regression. ANNs are powerful tools in estimation and classification and provide the flexibility to find both linear and non-linear relationships between independent and dependent variables. Moreover, when the input data set is large, working with ANNs is easier compared to many other estimation methods because ANNs can be trained data sample by data sample. In other words, all the data set is not required at the same time for training. This is a considerable advantage of ANNs, especially for oil and gas production analysis, because normally new data samples are provided over time and the ANN needs to be retrained.

The employed ANN (Figure 4.1) consisted of an input layer of four parameters, a hidden layer of 10 neurons and an output layer of five possible results. The input parameters to the network were chosen to be the mean, standard deviation, skewness, and kurtosis of each realisation. The target (or output), on the other hand, was the minimum number of TPMs that reduced the allocation error of the realisation to less than the chosen error specification. The five possible outputs were chosen to be one, two, three, four, and more than four tests per month.

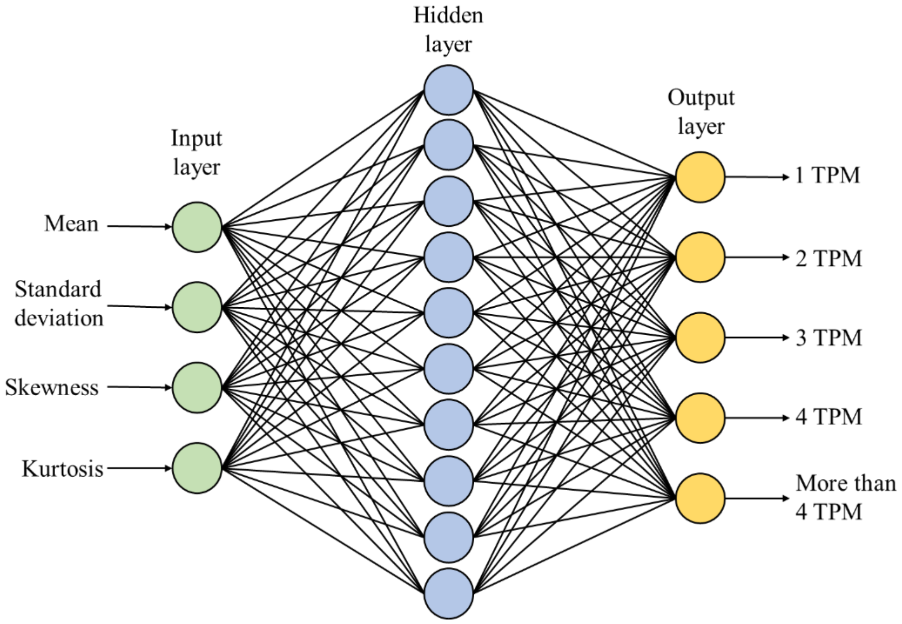

Figure 4.1: The structure of the employed artificial neural network in this research. TPM stands for test per month.

Figure 4.2 and Eq. 4.3 to 4.6 show how the weights and functions in the nodes of the network operate. The activation (transfer) function that has been employed in the hidden layer of this ANN is a $\mathrm{tansig}(\mathrm{x})$ function of Matlab (Eq. 4.3). This function is mathematically equivalent to $\tanh(\mathrm{x})$ and provides faster calculations. For the output layer, the Softmax Function (Eq. 4.5) has been used as the activation function. Softmax normalises the outputs of different classes and provides numbers between zero and one, which represent the probability of each input value being in a specific class.

$$T(n_i) = \frac{2}{1 + e^{-2n_i}} + 1 \tag{4.3}$$

$$n_i = \left(b + \sum_{j=1}^{M} W_j x_j\right)_i \tag{4.4}$$

$$S(\boldsymbol{n})_i = \frac{e^{n_i}}{\sum_{k=1}^{C} e^{n_k}} \tag{4.5}$$

$$\boldsymbol{n} = (n_1, n_2, \dots, n_C) \tag{4.6}$$

where n_i is the net input to the activation function of the i^{th} neuron of a network layer, $\boldsymbol{n}$ denotes the vector of all inputs to the activation function of neurons of the same layer, T stands for the *tansig* function (or equivalently, the *tanh* function), S represents the *softmax* function, M is the number of connections to each neuron coming from the previous layer, W_j denotes the weight of the j^{th} connection, x_j is the activation (i.e. final calculated value in a neuron) of the j^{th} neuron of the previous layer, b stands for the bias, C is the number of output classes.

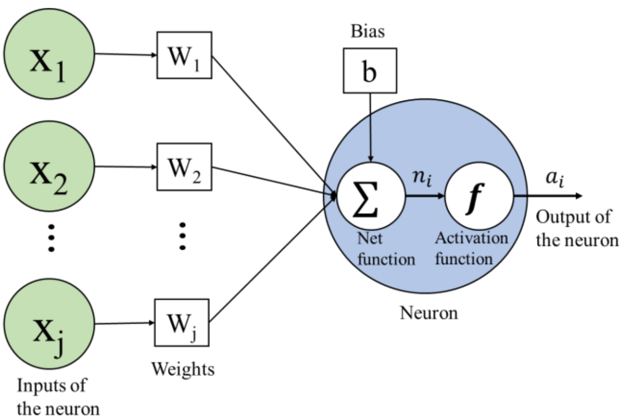

Figure 4.2: A neuron in the artificial neural network with its functions, inputs and outputs. Eq. 4.3 to 4.6 show the activation functions that have been used in this ANN.

70% of the total 360,000 realisations (252,000 realisations) were used to train the network using scaled conjugate gradient backpropagation, 15% of them (54,000 realisations) were used for the validation process, and the remaining 15% (54,000 realisations) was used for testing the network. All of these procedures were repeated several times for different error specifications and for each error specification the accuracy of the network was recorded. Finally, the performance of the neural network as a function of the error specification was obtained and reported.

In Chapter 3, it was shown that by increasing the number of TPMs, there is a better chance of reducing the average error of the entire field rather than to reduce the error of an individual well. Therefore, it was expected that finding the patterns of the data and the relations of inputs and targets would be easier for the neural network and it would have a better performance when the target is chosen based on the average allocation error of the entire field rather than the error of each well. Therefore, in the second phase of this research, the target was changed to 'the minimum number of flow tests per month on the wells of a field which can reduce the average allocation error of the field to less than an error specification'. For instance, if the output of the neural network is 'two' in this case, it means two tests per month must be performed on each individual well. The output is the same for all wells in the same field regardless of their different production patterns and the target is to reduce the average allocation error of the entire field to less than an error specification. Therefore, the entire procedure, which was explained for the first phase for individual wells, was repeated with the difference being that all the pieces of Matlab code were modified to provide outputs which were for the entire field (i.e. the average value of all 36 wells) rather than individual wells. The neural network was subsequently trained with the new targets and its performance was observed and reported as a function of the error specification of the field.

4.3 Results and discussion

Figure 4.3 illustrates the accuracy of the neural network to predict the minimum number of flow tests per month required to reduce the allocation error of the individual wells. The accuracy has been plotted as a function of the desired error specification. Error specification is referred to the maximum magnitude of measurement or estimation errors. As shown by Eq. 4.7, the accuracy of a neural network is defined as the fraction of the correct predictions of the network out of all of its predictions.

$$Acuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100 \qquad (4.7)$$

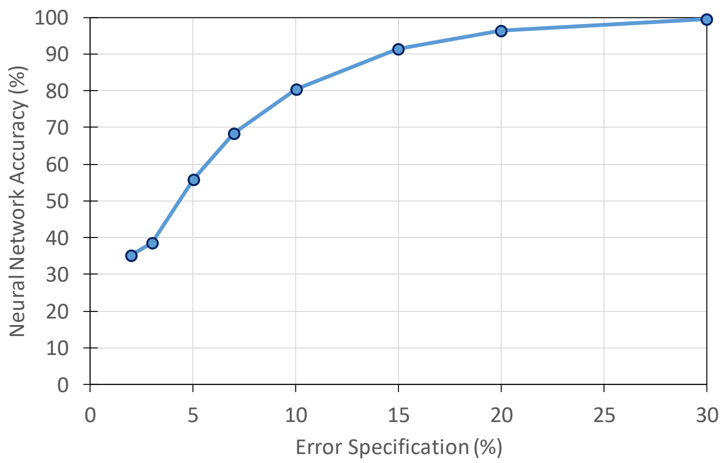

Figure 4.3: The accuracy of the artificial neural network as a function of the aimed error specification for individual wells.

Figure 4.3 shows the neural network has a good accuracy for the larger error specifications. As the error specification is reduced, however, the accuracy of the ANN predictions decreases. While the accuracy is 99.53% for a 30% error specification, when the error specification is chosen to be 2%, the accuracy drops to 35.14%. It means if we ask the neural network to provide us the minimum number of flow tests which is required to reduce the allocation error of the well to less than 30%, almost all of its predictions will be correct. Only one out of each three predictions of the ANN is, however, correct when 2% is chosen as the maximum allocation error permitted. Such a trend was expected since finding a relationship between the inputs and the targets is more difficult and complicated for the ANN when the error specification is reduced. In such a case, the range for the ANN target is small and therefore there is a lower probability of having a correct prediction in such a small range. It should be added that in this research, cost-benefit analysis has not been undertaken along with the data analysis. Including cost-benefit analysis can lead to even more valuable results and is suggested for a future research.

Although the result for small error specifications incorporate uncertainties, the ability of the ANN to provide good predictions in larger error specifications can have a significant application in the oil and gas industry. The errors in the allocation process are normally large and they can be as substantial as 50% (Sadri and Shariatipour 2019). The results in Figure 4.3 show that implementing the machine learning technique can reduce the errors of individual wells to less than 15% with 91.47% certainty, to less than 10% with 80.53% certainty, or to less than 7% with 68.53% certainty. These results can make the method interesting for the industry since achieving a maximum error of 15%, 10%, or 7% for individual wells means obtaining even smaller average errors for the entire field, which is a significant achievement.

For any single point in Figure 4.3, the entire process of training, validation, and testing has been undertaken separately. The following figures show the performance of the AAN in the aforementioned processes for an error specification of 2% as an example. Limited space precludes the inclusion of other error specification figures. The artificial neural network toolbox of Matlab uses Cross-Entropy as its cost function (Hudson Beale, Hagan and Demuth R2017a). Figure 4.4 shows the minimisation of the cross entropy as a function of the number of epochs for the case with the error specification of 2%. The best validation performance has been observed at epoch 192 with a cross entropy equal to 0.29.

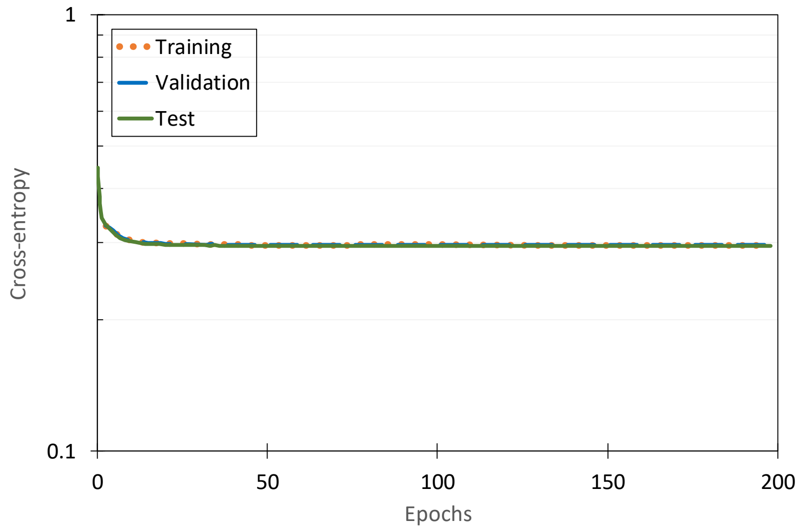

Figure 4.4: Cross-entropy as a function of the number of epochs for an individual well error specification of 2%.

Figure 4.5 shows the log-normal plot of the leaning gradient as a function of the number of epochs for the error specification of 2%. The initial gradient was 0.2 and the final gradient at epoch 198 reduced to 0.00036. The run time of the code, even for small learning gradients, remained reasonable. Figure 4.5 also shows the number of consecutive validation fails as a function of the number of epochs. The maximum number of consecutive validation fails is set as six as a default in the ANN tool box of Matlab to make sure that the ANN would not suffer from poor performance in predicting outputs of non-training data. The training process was therefore stopped at the epoch where six consecutive validations failed to occur. The training process was terminated at epoch 198, as shown in Figure 4.5. Validation data is used to prevent overfitting in the training process. When training is in process, the predictions of the ANN are also checked against validation (non-training) data. When the error of validation starts to increase while the error of training is still decreasing, overfitting is detected and the training process is consequently terminated.

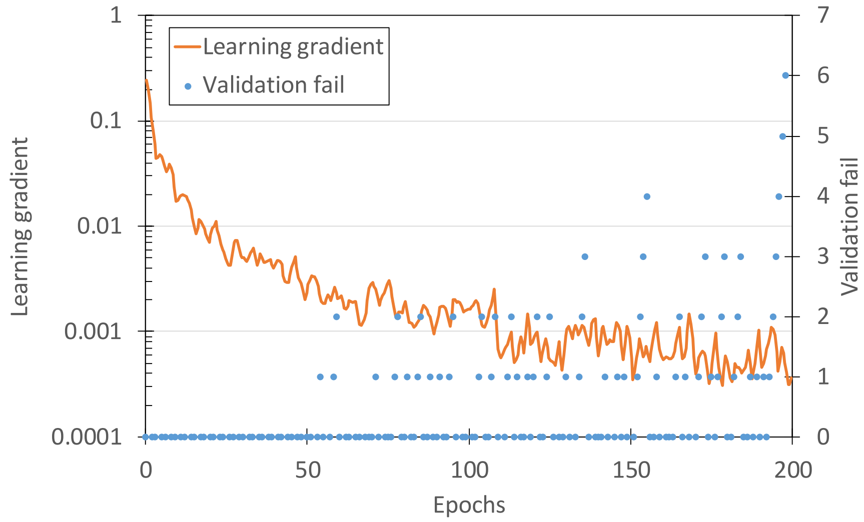

Figure 4.5: Learning gradient and validation check as a function of epochs for an individual well error specification of 2%.

4.3.1 Field average allocation error

In the first set of results (shown in Figure 4.3), the purpose of the ANN is to reduce the allocation error of individual wells. Therefore, the predicted number of TPMs by the ANN for different wells in the same field can potentially be different. In the second phase of this research, the ANN was trained to predict the minimum number of TPMs required to reduce the average allocation error of the entire field. Therefore, in this case, the number of TPMs suggested by the ANN is the same for all wells in the field. Although the wells, as a result, might have an allocation error more or less than the error specification, the aim is for the average allocation error of all of them to be under the error specification. The reason for undertaking the new training process is that reducing the average error of all wells is normally easier than reducing the error of individual wells. Our previous research study (Sadri and Shariatipour 2019) that was presented in Chapter 3, shows there is a clearer relation between increasing the number of flow tests and the reduction of the allocation error when the aim is the average error of the field instead of the error of the individual wells. Therefore, it was expected that the ANN would be able to provide more accurate predictions when its goal is to reduce the field average error instead of the error of individual wells.

The same ANN with the same inputs but different targets was trained in the second phase of the research to test this idea. The target for the ANN in this phase was 'the minimum number of flow tests per month that can reduce the average allocation error of the field to less than an error specification'. The training, validation, and testing processes were undertaken for different error specifications, similar to the first phase. The accuracy of the ANN as a function of the error specification is shown in Figure 4.6.

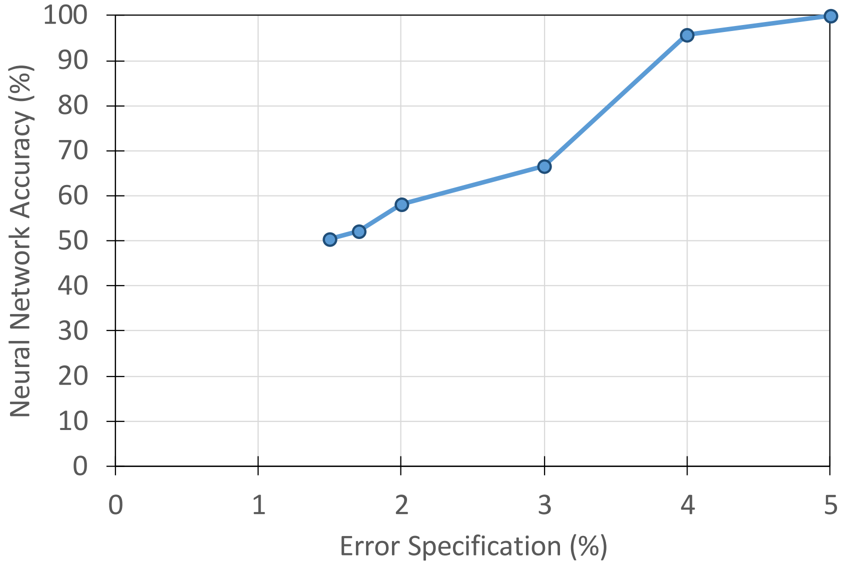

Figure 4.6: The accuracy of the artificial neural network as a function of the aimed error specification for an entire field. It shows how accurate the ANN has been in estimating the minimum number of flow tests in a month required to reduce the average allocation error of the entire field to less than the error specification.

Figure 4.6 shows that when the aim is the field average error, the predictions of the ANN are more accurate. Although the same trend as in Figure 4.3 is observed, the accuracy of the ANN is always greater for the same error specifications in Figure 4.6. For instance, the accuracy is seen to be 58.09% and 99.89% for 2% and 5% error specification, respectively, in Figure 4.6 while it was equal to 35.14% and 55.82% for the same error specifications in Figure 4.3. As seen in Figure 4.3 an accuracy of over 95% had been achieved in more than 18% error specification, while in Figure 4.6 this accuracy was attained for error specifications greater than only 4%.

As an example of the performance of the ANN in the second approach, Figure 4.7 and 4.8, which belong to the training case with the field average error specification of 2%, have been presented below. Figure 4.7 shows the cross entropy as a function of the number of epochs. The best validation performance was observed at epoch 34 with a cross entropy equal to 0.17.

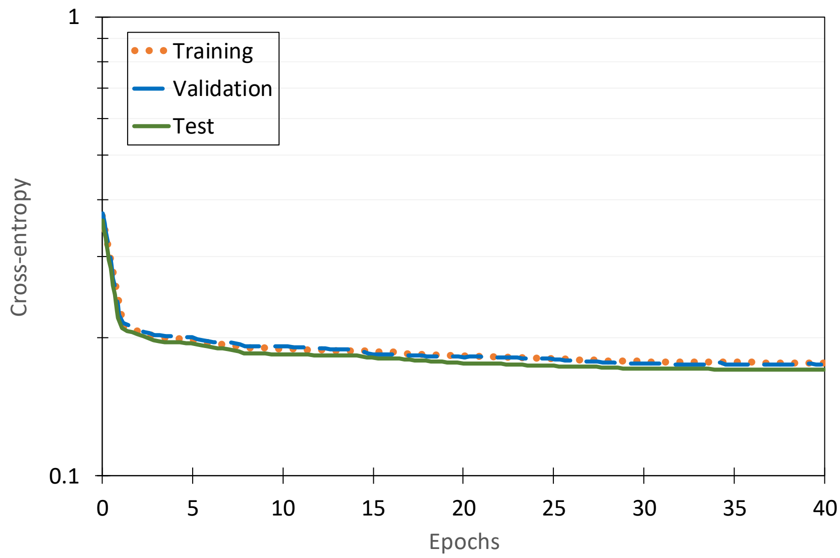

Figure 4.7: Cross-entropy as a function of the number of epochs for an average field error specification of 2%. The best validation performance has happened when the cross-entropy has been 0.07461 at epoch 34.

Figure 4.8 shows the leaning gradient as a function of the number of epochs and also illustrates the number of consecutive validation fails for each epoch. The training process was terminated at epoch 40. The final learning gradient at this epoch was 0.00302.

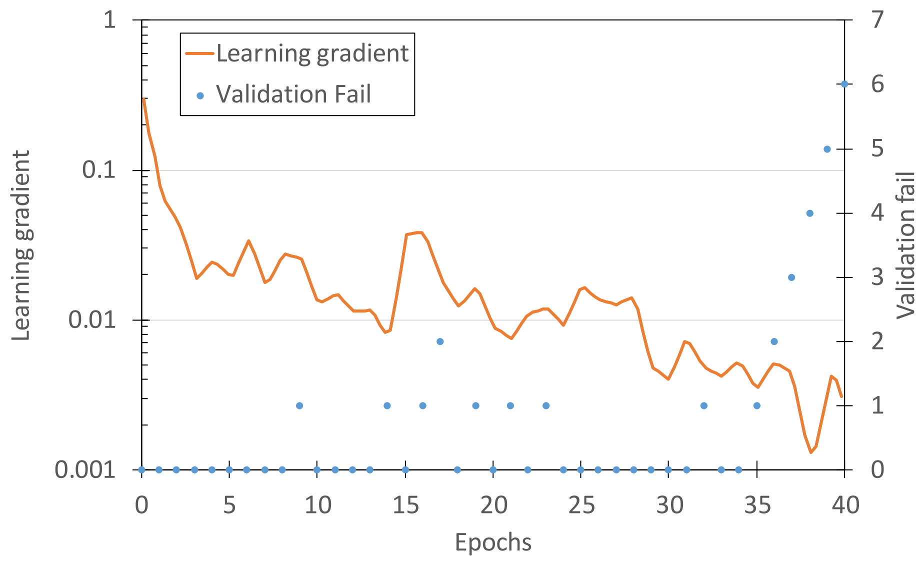

Figure 4.8: Learning gradient and validation check as a function of epochs for an average field error specification of 2%. The number of consecutive validation fails has reached six at epoch 40 where the gradient has been 0.0030239.

4.3.2 A discussion on both approaches

We can see that for the two different approaches outlined above, each has their own advantages and disadvantages. In the first approach (Figure 4.3), the accuracy of the ANN is less (disadvantage) but its predictions help operators to make decisions for each well individually (advantage). In the second approach (Figure 4.6), the decision for all wells is similar (disadvantage) but there is more certainty in the decisions made since the ANN is more accurate (advantage). Therefore, this question remains unanswered as which approach is better to employ in an oil and gas field. The answer to this question surely depends on the situation of each individual field. If the production flow rates of different wells exhibit similar or a close range of fluctuation and stability, the second approach is probably enough to help in making decisions about the required number of flow tests for the wells. If some wells have larger fluctuations, instability, water production, or any other significant production uncertainty, however, the decision for those wells must be made individually. In such a case, considering the outputs of both approaches might be helpful in making the final decision.

Although the proposed machine learning technique in both of approaches exhibits acceptable accuracy over some ranges, large uncertainties still remain in other ranges of the error specification. It should be mentioned that this work is not suggesting that the technique can fully replace the current procedures for making decisions for the regularity of flow tests, but proposing it as a supplementary tool to help in the decision making process. The current procedures are mainly dependent on the experience of the operators, something that is definitely needed when applying this new method in a field. All other production conditions found in the wells such as their water cut, gas-oil ratio, or their production history, must also be considered. Another factor is the difficulty or the cost of undertaking more flow tests. Considering all of these aspects is still not a task that can completely be given over to a computer.

The main purpose of this chapter has been to propose the machine learning technique and show that it has the potential to reduce the uncertainty in the oil and gas production data. Improving the accuracy of the technique for smaller error specifications can be suggested for a future research project. A potential solution for it can be the addition of an extra input to the ANN that represents the trend of production for each well. A proper method to quantify the general trend of production must, however, be found first.

4.4 Conclusions

In this chapter, a machine learning approach was employed to mitigate allocation uncertainties in oil and gas fields. An artificial Neural Network (ANN) was therefore trained to find the minimum number of flow tests required to achieve errors less than a target value. The target of the ANN was a desired maximum error (error specification) for the individual wells in the first phase of the research and a desired maximum average error for the entire field in the second phase. The results of both phases show that the outputs of the ANN can be useful in making decisions about the regularity of flow tests. In both phases, the accuracy of the predictions of the ANN decreased when the target error specification was reduced. In both cases, for larger error specifications, however, the accuracy was found to be high. The ANN had a higher accuracy in the second phase (i.e. when its target was the maximum average error of the entire field). For error specifications greater than 4% in this phase, the accuracy was over 95%. The same accuracy was achieved when the error specification was between 15% to 20% in the first phase.

Chapter 5: Effect of flow measurement uncertainties on reservoir management

Chapters 3 and 4 focused on hydrocarbon accounting and allocation errors and explained a method to reduce the uncertainty in the production data. Chapter 5, however, is dedicated to investigating the effects of flow measurement uncertainties on two important tools of reservoir management: history matching and well testing.

History matching and well testing provide valuable information for the process of reservoir management and in decision making. They are therefore indirectly effective on the economic recovery of oil and gas. This chapter investigates the potential impacts of flow measurement uncertainties on the outcomes of these two industry exercises and provides recommendations for mitigating the uncertainties. The first section of the chapter (Section 5.1) is on history matching and the second section (Section 5.2) focuses on well testing.

5.1 History matching‡

History matching is the process of modifying a numerical model (representing a reservoir) in the light of observed production data. In the oil and gas industry, production data is employed during a history matching exercise to reduce the uncertainty in associated reservoir models. However, production data, normally measured using commercial flow meters that may or may not be accurate depending on factors such as maintenance schedules, or estimated using mathematical equations, inevitably has inherent errors. In other words, the data which is used to reduce the uncertainty of the model may have considerable uncertainty in itself. This problem is exacerbated for gas condensate and wet gas reservoirs as there are even greater errors associated with measuring small fractions of liquid. The influence of this uncertainty in the production data on history matching has not been addressed in the literature so far. In Section 5.1, the effect of systematic and random flow measurement errors on history matching is investigated. In order to do that two case studies based simulations of an oil reservoir and a wet gas reservoir have been undertaken.

5.1.1 Introduction

The knowledge of reservoir management has dramatically improved. Managing hydrocarbon reservoirs to maximise the profit from them, which had a limited knowledge and involved just simple calculations in the early years of the oil and gas industry, has become a complicated dynamic process of setting goals, decision making, implementing, monitoring, analysing data, and modifying decisions (Satter, Varnon and Hoang 1994). Reservoir management in its present form needs a multidisciplinary approach and the

‡ The contents of Section 5.1 have been extracted from the following paper:

Sadri, M., Shariatipour, S., Hunt, A. and Ahmadinia, M. (2019) 'Effect of systematic and random flow measurement errors on history matching: a case study on oil and wet gas reservoirs'. Journal of Petroleum Exploration and Production Technology, 9(4).

The candidate developed the methodology, undertook the required simulations, wrote the Matlab codes, analysed the results, and prepared the article. The history matching exercise has been undertaken by the help of Schlumberger ECLIPSE software package. The required ECLIPSE data files and reservoir models were developed by the candidate. Seyed M. Shariatipour supervised the research and Masoud Ahmadinia helped in preparing some graphs in the article.

integrated application of different technologies and professional software. In this process, a large amount of data is recorded and analysed and engineers need to deal with numerous uncertainties. Trice Jr and Dawe (1992), Satter, Varnon and Hoang (1994), Al-Hussainy and Humphreys (1996), and Thakur (1996) have explained principles of reservoir management in their publications. Recently, the concept of Closed-Loop Reservoir Management (CLRM) has been introduced in the literature and several studies have been published on this title (Barros, Van den Hof and Jansen 2016; Hanssen, Codas and Foss 2017; Jansen et al. 2005; Jansen, Brouwer and Douma 2009; Lorentzen, Shafieirad and Naevdal 2009; Wang, Li and Reynolds 2009). CLRM (Figure 5.1) is a combination of history matching and model-based optimisation and its aim is to change reservoir management from a periodic to a near continues process (Jansen, Brouwer and Douma 2009). As shown in Figure 5.1, history matching plays an important role in the management process as it has a direct effect on the reservoir model and an indirect effect on the decisions and plans for the reservoir through its impact on the model and on the reservoir optimisation. Therefore, perhaps we can name history matching as 'the heart of CLRM' since it synchronises the two reservoirs (actual reservoir and reservoir model) in the loop.

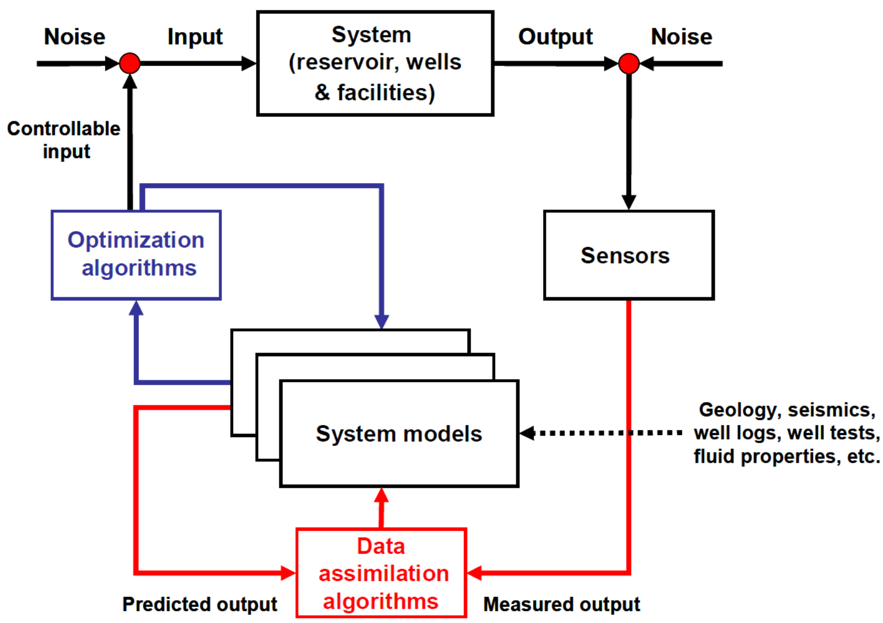

Figure 5.1: Closed-Loop Reservoir Management (Jansen, Brouwer and Douma 2009).

History matching is an inverse problem. In a forward problem, the output of a system is calculated based on the characteristics of the system (Figure 5.2). In an inverse problem, the system is unknown and the observed output of the system is used to determine its characteristics (Kirsch 2011). However, the output data usually has inherent errors that affect the calculations. As a consequence, the obtaining system characteristics might be different from the actual ones. In history matching, the system is a reservoir and the output is its production data. The difference is that the reservoir is not completely unknown and an initial model is available based on the information obtained from other sources such as seismic data, well testing, and laboratory experiments on the characteristics of the reservoir rock and fluid samples. However, since this initial model is highly uncertain, the production data is used to mitigate the model uncertainties. History matching is widely used in the oil and gas industry and many different methods of performing it have been published in the literature (Chakra and Saraf 2016; Hamdi et al. 2015; Makhlouf et al. 1993; Obidegwu, Chassagne and MacBeth 2017; Oliver and Chen 2011; Oliver, Reynolds and Liu 2008; Tunnish, Shirif and Henni 2018).

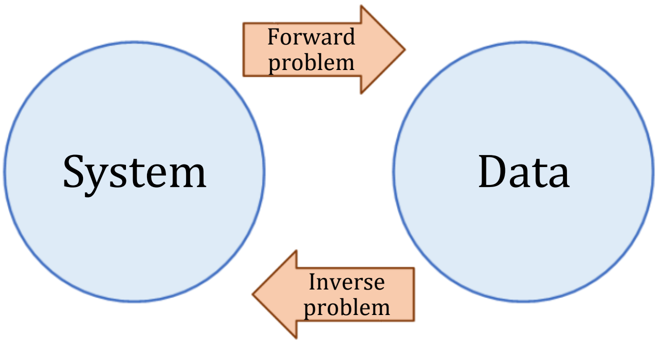

Figure 5.2: Forward and inverse problems. In an inverse problem, such as history matching, the characteristics of an unknown system are estimated based on its observed output data.

As stated above, production data is employed in history matching to reduce the uncertainty of the reservoir model. However, production data (oil and gas production rates, water cuts, and downhole or wellhead pressures) similarly has inherent uncertainty. Any observed data inevitably contains errors and the extent of an error depends on the estimation method or the measurement equipment which is employed to gather the data.

Therefore, history matching does not merely deal with the uncertainty in the system, but also with the uncertainty in its own inputs which can potentially affect the results. Although different types of reservoir uncertainty have been comprehensively studied previously (Abdollahian, Tadayoni and Junin 2018; Babak and Deutsch 2008; Habib et al. 2017; Mozaffari et al. 2017; Stephen and Macbeth 2008; Tavassoli, Carter and King 2004; Xu et al. 2018), the uncertainty in the observed data has not drawn the attention of researchers so far.

Oil, gas, and water production flow rates are the main observed data sets used in history matching. In different oil and gas fields, different methods are used to record production flow rates. As it was mentioned in Chapter 4, in many cases, production from different wells is commingled and the total production is sent to the separation unit. The single-phase stream flowing out of the separation unit is measured by flow meters subsequently. Having the total flow rate of all wells, engineers then allocate flow rates to each well based on allocation factors. Allocation factors are normally determined based on flow rate measurements from intermittent tests on individual wells. To perform the tests, operators disconnect individual wells from the main production pipe and send the flow rate of the well to a test separator. As a result, they can measure production flow rates for individual wells and hence calculate the proportion of the production of each well to the total production. The gap between two tests varies for different fields but normally the test is not undertaken more than once a month. The uncertainty in allocation methods is large since the actual proportion of the production of each well to the total production does not remain the same as the measured one. Moreover, there is no guarantee that the production conditions over the test time are the same as the conditions during normal production. The principles of different methods of allocation have been explained by the Energy Institute (2012). The focus of many publications on allocation is its application in hydrocarbon accounting (Cramer et al. 2011; Kaiser 2014; Pobitzer, Skålvik and Bjørk 2016). There is a dearth of publications on the application of allocation data in reservoir analysis, reservoir management and history matching. Among the latter publications is the work of Bergren, Lagerlef and Feldman (1997). They reported their successful experience in employing an allocation system including computers, communications hardware, and software for both hydrocarbon accounting and reservoir management for

Prudhoe Bay oil field in Alaska. In another research study, Marshall et al. (2019) investigated the effect of random errors in production data on forecasted hydrocarbon recovery. They showed that in a case where the reservoir model is selected incorrectly due to the errors, it can have a significant effect on the estimated recovery factor and reservoir parameters which are obtained in well testing.

Another method that is currently employed in some fields, especially for offshore ones, is the use of multi-phase flow meters (MPFM) for individual wells. In this method, although the production data of individual wells is recorded with a higher accuracy the data still has some errors. The error is larger for gas reservoirs where gas void fractions are greater than 90% (Leeson, Heering and Dykesteen 2001). MPFMs normally struggle to recognise small fractions of liquid. Therefore, for a gas void fraction greater than 90%, the inaccuracies rapidly rise with the increasing percentage of gas. Generally, flow measurement in wet gas and gas condensate reservoirs is more challenging than oil reservoirs and the flow measurement data for gas reservoirs normally includes more uncertainty (Letton and Hall 2012). Falcone et al. (2002) have undertaken a thorough research on the applications of MPFMs in the oil and gas industry. A book on principles and applications of MPFMs has been published based on their research later (Falcone, Hewitt and Alimonti 2009).

Flow meters exhibit two types of error: systematic and random. Random errors shift each measurement by a random amount up to the error specification of the flow meter in a random direction. Therefore, different measured values are obtained when a measurement is repeated several times for a constant quantity. Random errors have no pattern and they are unpredictable. Although there is no way to have zero random error and the existence of random errors in the measured data is unavoidable, it is possible to increase the precision of the flow meter and reduce the error specification by using new flow metering technologies (Tombs et al. 2006). Random errors tend to be normally distributed. They can be analysed statistically and explained in terms of their mean (Eq. 2.6) and standard deviation (Eq. 2.7).

In this chapter, the word ‘precision’ has been used to describe the magnitude of the random errors qualitatively. In technical terms, a more precise flow meter has smaller random errors. On the other hand, systematic errors are normally predictable and they usually exhibit a pattern. Systematic errors shift all of the measurements in the same direction and by the same magnitude. The error is typically constant or proportional to the true value of the measured quantity. Since the shift of the data is in one direction, systematic errors do not have a zero mean. Another difference between systematic and random errors is that systematic errors can be avoided by identifying and eliminating their causes, these primarily being improper calibration and poor maintenance. Flow meters are normally subjected to high pressure and temperature, friction with fluids, and deposition of asphaltene, wax, and scale. These factors and other similar environmental impacts change the operational conditions of a flow meter (Lindsay et al. 2017; Liu et al. 2017). Therefore, they need to be calibrated and maintained regularly to be able to work within the desired error specifications and it takes a part of annual operational costs of oil and gas companies. The term that has been used in this article to explain the extent of systematic error is "trueness". "Accuracy" is another more general technical term that includes both types of errors. An accurate flow meter is a flow meter with a high precision and trueness (i.e. low systematic and random errors). The terminology is the same as most technical articles on errors. Figure 5.3a shows the different possible states of a data set in terms of its trueness and precision. More information about systematic and random errors has been presented by Taylor (1997). Figure 5.3b shows the data sets which were employed for the oil cases in this research. As the comparison between Figures 5.3a and 5.3b suggests, each data set based on its random and systematic error represents a different level of precision and trueness. More details about Figure 5.3b and the generation of the data sets have been presented below in the oil reservoir section of this chapter.

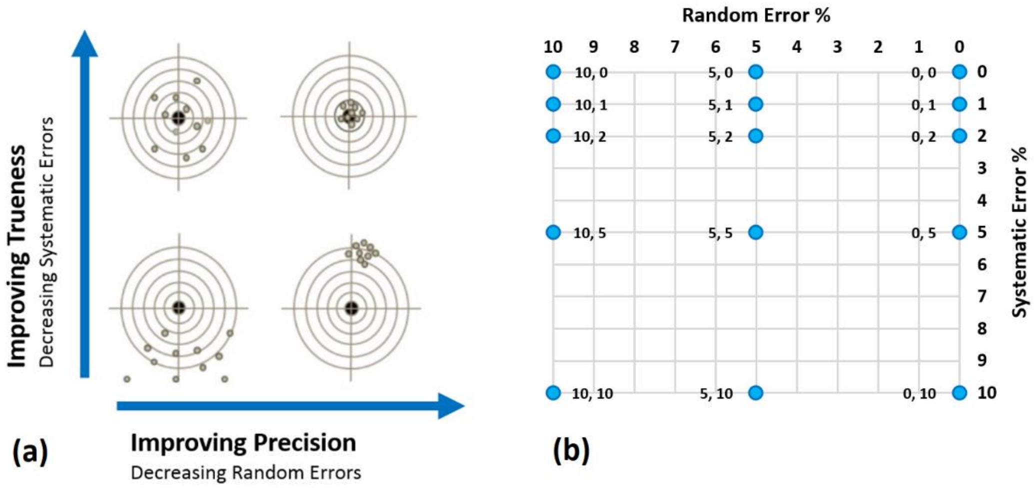

Figure 5.3: (a) Different states of a data set in terms of its trueness and precision and; (b) the error values of the data sets employed in this research (each blue point represents both systematic and random error values for one of the data sets). The defined data sets in Figure 5.3b represent different states in Figure 5.3a.

So far, the focus of many oil and gas industry researchers and professionals has been on investigating the effects of flow measurement errors on custody transfer and fiscal measurement (i.e. hydrocarbon accounting). Custody transfer is when oil or gas is transferred from one operator to another. Fiscal measurement is a more general term. It includes any flow measurement used to determine the financial value of the delivered oil and gas. In these cases, the accuracy of the measurements is indeed important. Therefore, countries have precise regulations and standards for custody transfer and fiscal measurement that determines the acceptable error ranges. As a result, operators use approved flow meter technologies to meet these regulations. Several publications about flow measurement regulations for custody transfer and fiscal measurement are available online. For instance, Guidance Notes for Petroleum Measurement (2015) explains the regulations in the UK. So far, the role of flow measurement in reservoir management has not drawn the attention of professionals as much as its role in fiscal measurements. However, the new methods of reservoir management are strongly dependent on data analysis and as a result, they are highly sensitive to the quality of the data. As shown in Figure 5.1, the output data from the actual reservoir is inevitably noisy and this noise and any other error in the observed data impacts on the whole process of reservoir management, including history matching and reservoir optimisation. The quality of the data also indirectly affects the hydrocarbon recovery by affecting the reservoir management and decision-making process. Therefore, it is important to have an idea of the required quality for the data which can guarantee a good management over the reserves and maximised oil and gas recovery. In this chapter, the effect of systematic and random flow measurement errors on history matching has been investigated. Production data is the main group of data which is employed in reservoir management. Investigating the effects of flow measurement errors in production data on history matching opens up new ways to undertake further research on the effects of flow measurement errors on reservoir management and hydrocarbon recovery. In a previous study, we showed that flow meters which have errors just in one direction (i.e. positive or negative) cause more errors in the results of history matching compared to when they have errors in both directions (Sadri, Shariatipour and Hunt 2017). In this chapter, as a more general investigation, the effect of systematic and random flow measurement errors on history matching in an oil and a wet gas reservoir is addressed. In the following lines, first, the methodology of this work including the details of the simulation models, the prepared Matlab code, and the error data sets has been explained, the results presented and discussed, and finally the conclusions and suggestions have been briefly stated.

5.1.2 Methodology

Two case studies on two synthetic reservoirs, an oil and a wet gat reservoir, have been undertaken in this research to investigate the effects of systematic and random flow measurement errors on history matching.

5.1.2.1 Oil Reservoir

For the oil reservoir case, a reference reservoir model with the characteristics shown in Table 5.1 was employed in the Schlumberger ECLIPSE simulator to produce reference production data (oil, gas and water production rates) over ten years.

Table 5.1: Characteristics of the reference oil reservoir. These characteristics were employed to build the reservoir model.

Initial reservoir pressure	304.20 bar
Porosity	0.18
Horizontal permeability	60 mD
Vertical permeability	10 mD
Saturation pressure of reservoir hydrocarbon	386.11 bar
Density of oil at the surface conditions	721 kg/m^3
Density of water at the surface conditions	1009 kg/m^3
Density of Gas at the surface conditions	1.12 kg/m^3

The data was then imported into the Matlab software and a Matlab code generated 15 data sets with different ranges of systematic and random error, as shown in Figure 5.3b. 10% was chosen as the highest error in each category (random or systematic). It means the highest error that was possible to happen for this case was 20%. These data sets were later used as observed production data in history matching. Random errors have been produced using randomly generated numbers within the specified ranges (i.e. 0%, 5%, and 10%) in both the positive and negative directions. For instance, when the error specification was 5%, random errors could take any value between -5% to +5%. However, systematic errors were set to fixed percentages (i.e. 0%, 1%, 2%, 5%, and 10%) and their values were proportional to the reference values. After creating the data sets, the Matlab code generated RSM files (a format which can be imported into ECLIPSE for further simulations and history matching) including the observed data. The code can also perform a statistical analysis and report the results in terms of the mean (Eq. 2.6) and standard deviation (Eq. 2.7) of the data sets in an Excel file. The statistical information about the data sets used in this work is shown in Table 5.2.

Table 5.2: The details of the errors in different data sets which were used in the history matching. The data sets in the lighter shaded rows have been used for both oil and wet gas reservoirs and the data sets in the darker shaded rows have been used only for the wet gas reservoir. These data sets in addition to the reference production data have been employed to generate the observed data in the history matching.

Data Set Number	Systematic Error (%)	Random Error (%)	Mean of Errors (%)	Standard Deviation of Errors (%)
1	1	0	1.00	0.00
2	2	0	2.00	0.00
3	5	0	5.00	0.00
4	10	0	10.00	0.00
5	20	0	20.00	0.00
6	0	5	-0.07	2.92
7	1	5	0.93	2.92
8	2	5	1.93	2.92
9	5	5	4.93	2.92
10	10	5	9.93	2.92
11	20	5	19.93	2.92
12	0	10	-0.13	5.84
13	1	10	0.87	5.84
14	2	10	1.87	5.84
15	5	10	4.87	5.84
16	10	10	9.87	5.84
17	20	10	19.87	5.84
18	0	20	-0.27	11.68
19	1	20	0.73	11.68
20	2	20	1.73	11.68
21	5	20	4.73	11.68
22	10	20	9.73	11.68
23	20	20	19.73	11.68

In the next stage of the work, the observed data (i.e. reference data with errors) was used in history matching to modify an uncertain reservoir model. The only differences between the uncertain model and the reference model were the values for porosity and permeability. These values were 0.28 and 40 mD for the uncertain model, respectively. Finally, the data from the modified model was compared to the data from the reference model to show the effect of the systematic and random flow measurement errors on the results of the history matching (i.e. estimated porosity, permeability, oil and gas production). This process was undertaken for all the data sets with different random and systematic errors and the results were compared and analysed. The systematic and random errors were defined so that they represent different states of a flow meter (or allocated data) based on its trueness and precision, as shown in Figure 5.3. The density of the data sets around (0,0) point was higher because in high precision and high trueness even a one percent change in the error might have a significant effect. Also, the number of the chosen values for systematic error was greater than random errors because initially we expected to see a more significant effect due to systematic errors; an expectation which was later proved to be correct based on the results.

In this chapter, the traditional method of history matching has been used to modify the uncertain reservoir model. In the traditional method, the best match between the simulation results and the observed data is used for reservoir model modifications. The best match is obtained by performing the simulations and comparing the simulation results to the observed data in an iterative procedure. In each iteration, the sum of the squared residuals (the difference between the observed and simulated values) is calculated and compared to that of the previous iteration. The aim of this method (least-squares method) is to minimise the mentioned calculated value. When the difference between two calculated values in two consequent iterations is less than a specified value (e.g. 0.1), the iterative procedure is stopped and the match is considered as the best possible one. Since the parameters of the reservoir model (in our case the porosity and permeability) are updated in each iteration to gain a better match, in fact, the model modification is also performed in the iterative procedure at the same time. Therefore, the model of the last iteration is considered the most up to date reservoir model and used for production forecast. We refer to this model as the “modified model” in this chapter.

Porosity and permeability were chosen as the parameters to be modified because they are among the most important characteristics of a reservoir that can affect its production forecast. The other characteristics of the uncertain model were kept the same as the reference model to make the problem simple and enable us to see the pure effect of flow measurement data on the modifications and future forecast. In the final step, the porosity and permeability of the modified model and the oil and gas production forecast for the next 20 years have been compared to those of the reference model and the error of these parameters has been reported to show the effect of flow measurement errors on history matching. The errors in porosity, permeability, and forecasted oil and gas production were calculated based on Eq. 5.1.

$$E_P = \left| \frac{v_{est} - v_{ref}}{v_{ref}} \times 100 \right| \tag{5.1}$$

where E_P is the parameter error (%), v_{est} is the estimated parameter value, and v_{ref} is the reference parameter value.

Figures 5.4a to 5.4c show the obtained matches between the simulation results (oil, gas and water production rates) and the data set with 5% systematic error and 10% random error after the history matching. The results of the reference oil reservoir have also been illustrated for comparison. The gap between the results of the history matching and the reference reservoir clearly show that the errors have affected the history matching.

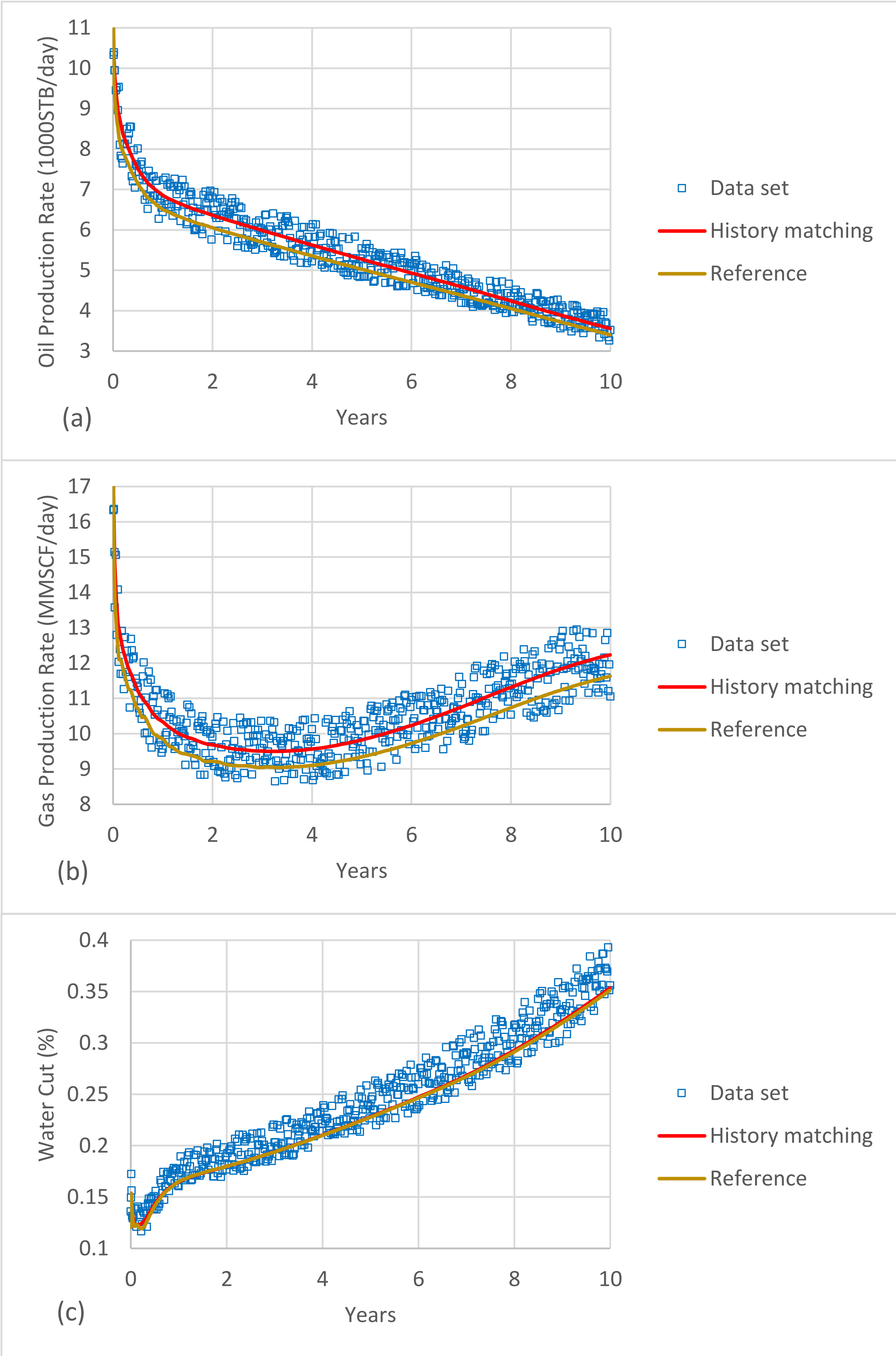

Figure 5. 4: The history matching results of the oil reservoir for: (a) oil; (b) gas, and; (c) water production rates based on the data set with 5% systematic and 10% random error.

5.1.2.2 Wet Gas Reservoir

The same procedure for the oil reservoir was undertaken for a synthetic wet gas reservoir, with characteristics shown in Table 5.3. As stated earlier, measuring flow rates in wet gas reservoirs is more challenging than oil reservoirs due to the small fraction of producing liquid compared to gas. Therefore, there is normally more uncertainty associated with observed data for wet gas reservoirs than oil reservoirs (Letton and Hall 2012). To address this issue in the research, the range of systematic and random flow measurement errors in the observed data for the wet gas reservoir was increased to 20%. As a result, 23 observed data sets with different values of systematic and random flow measurement errors were employed in the history matching for the wet gas reservoir. The statistical information of the data sets is shown in Table 5.2.

Table 5.3: Characteristics of the reference wet gas reservoir. These characteristics have been employed to build the reservoir model.

Initial reservoir pressure	302.06 Bar
Porosity	0.18
Horizontal permeability	60 mD
Vertical permeability	10 mD
Density of liquid hydrocarbon at the surface conditions	640 kg/m^3
Density of water at the surface conditions	1009 kg/m^3
Density of Gas at the surface conditions	0.84 kg/m^3

5.1.3 Results and discussion

Figures 5.5a to 5.5d show the final errors in the oil reservoir history matching results from different observed data sets. The figures illustrate the errors in the simulated oil production, gas production, porosity and permeability, respectively.

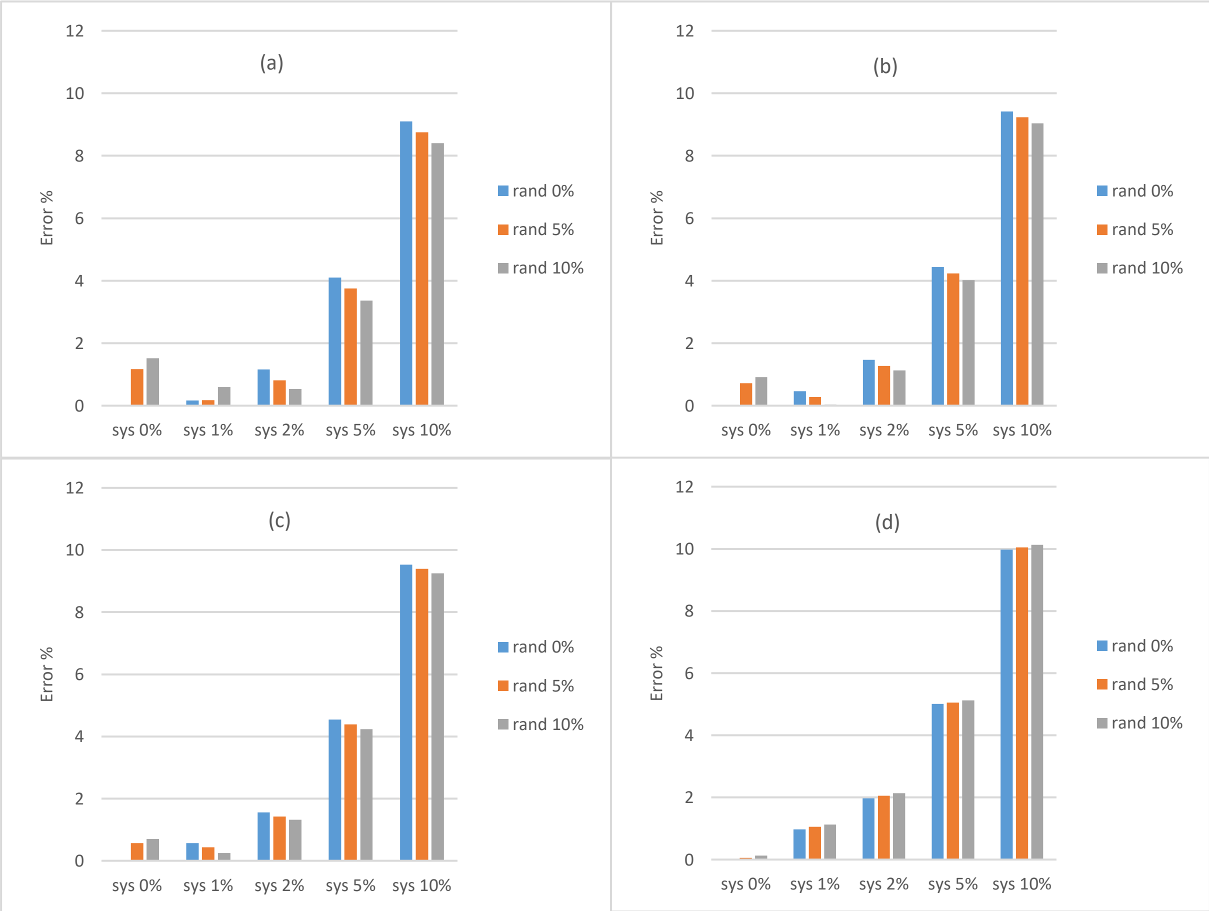

Figure 5.5: Final errors of the history matching in estimating: (a) oil production; (b) gas production; (c) porosity; and (d) permeability for all the employed data sets for the oil reservoir ("sys" and "rand" refer to systematic and random errors, respectively).

The plots clearly illustrate the substantial effect of systematic errors on history matching, with a contradictory suggestion that the effect of random errors is insignificant. While history matching errors of all of the considered parameters (oil production, gas production, porosity, and permeability) are less than 2% when systematic error is 0% and random error is 10%, they increase to more than 9% for the opposite case when systematic error is 10% and random error is 0%. Therefore, based on the results, an increase in the systematic error (i.e. decreasing trueness) is seen to cause a significant increase in the history matching error for all the investigated parameters. However, all the simulation results show that increasing random error (i.e. decreasing precision) does not have a major effect on history matching. A possible explanation for this observation is that random errors have a distribution in both the positive and negative directions. Therefore, they dampen the effect of each other. Systematic errors, however, are distributed in only one direction (positive or negative). Unexpectedly, for the oil production, gas production, and porosity, we see a decrease in the history matching errors with the increase of the random error when the systematic error is more than 2%. Therefore, the results show that in this region, not only does the lower precision of the flow meter not increase the error in history matching, but the results are seen to be improved by a dampening in the effect of the systematic errors. This dampening effect can be a consequence of the even distribution of the random errors.

The results of three out of four parameters (oil production, gas production, and porosity) show a decreasing trend in the history matching error when the systematic error is small (i.e. from 0% to 1%). The trend then increases for larger systematic errors (i.e. from 2% to 10%). Therefore, it can be concluded that for these three parameters the effect of random error is dominant when the systematic error is small (i.e. less than 2% in this case). However, beyond two percent, the systematic error has a dominant effect. The plot for the fourth parameter (permeability), though, shows a continuous increase of history matching error for all the range of the systematic error (i.e. from 0% to 10%). In contrast to the other three parameters, increasing the random error also leads to a continuous increase in the permeability error for the whole range. All these results, in addition to the higher value of permeability errors compared to the errors of the other parameters, suggest that the estimated permeability is more sensitive to flow measurement errors. Therefore, for the permeability, even the effect of a one percent increase in the systematic error can clearly be seen in the plot.

Figures 5.6a to 5.6d show the final errors in the history matching results for the gas reservoir causing from different observed data sets. Similar to the oil reservoir, the plots show errors in hydrocarbon liquid production, gas production, porosity, and permeability.

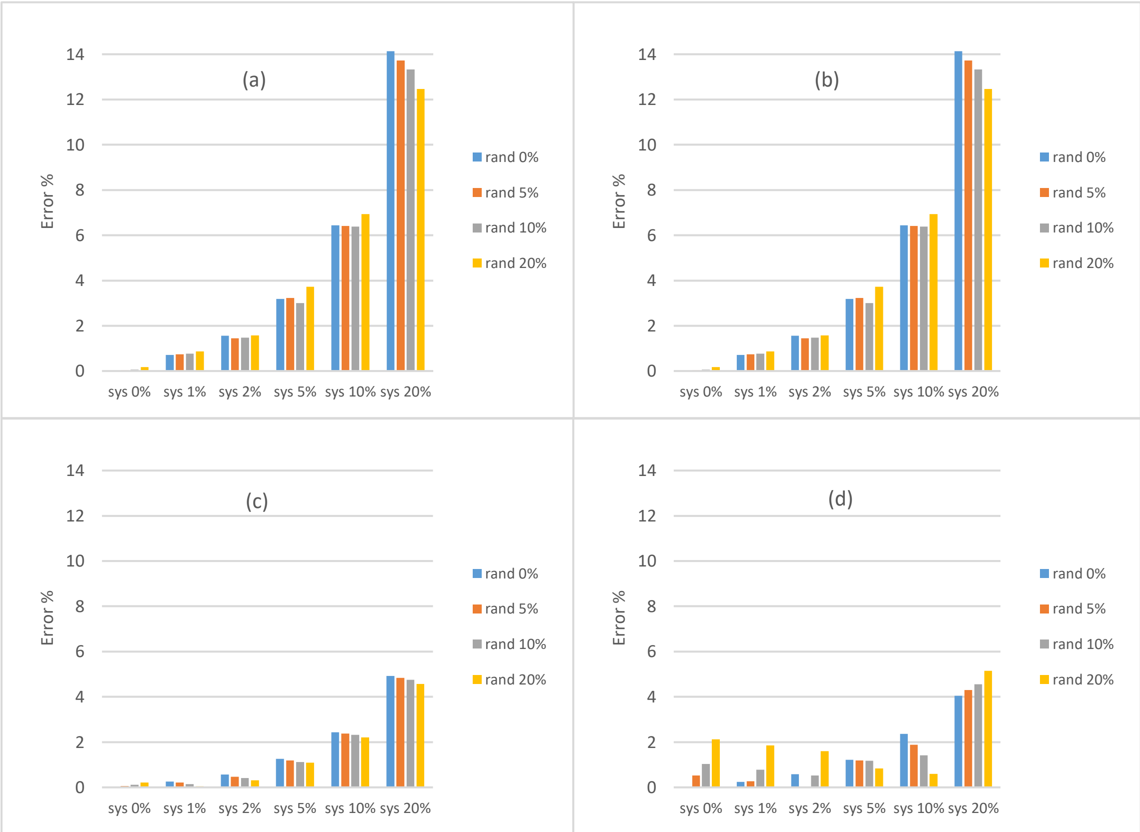

Figure 5.6: Final errors of the history matching in estimating: (a) hydrocarbon liquid production; (b) gas production; (c) porosity; and (d) permeability for all the employed data sets for the wet gas reservoir ("sys" and "rand" refer to systematic and random errors, respectively).

In wet gas reservoirs, the hydrocarbon under the reservoir conditions (reservoir pressure and temperature) is in the gas phase. The liquid hydrocarbon appears in their production as a result of the low pressure on the surface. Since no liquid hydrocarbon is formed and accumulated in the formation around the wells (inside wet gas reservoirs) during production, the composition of the producing hydrocarbon does not change over time. Therefore, in contrast to oil or gas condensate reservoirs, the gas to liquid ratio (GLR) remains the same during the life of a wet gas reservoir. As a result of the constant GLR in wet gas reservoirs, the error in hydrocarbon liquid and gas production forecast is exactly the same because their ratio remains the same. This is the reason why Figures

5.6a and 5.6b show similar errors for the liquid and gas production forecasts. More information about characteristics of wet gas reservoirs have been presented by Ahmed (1989), McCain (1990) and Dandekar (2013).

The results of the history matching exercise for the wet gas reservoir generally agree with the results obtained from the oil reservoir. Similar to the previous case, the effects of the random flow measurement errors were seen to be insignificant but the effect of the systematic errors are seen to be considerable. In considering all the plots in Figures 5.5 and 5.6, it is observed that there is no general trend in the changes of the history matching error as a function of the random error. It occurs due to the nature of random errors since they unsystematically deviate the data points towards both directions. Therefore, the total effect of the random errors may boost the effect of the systematic error if they are in the same direction or balance it if they are in opposite directions. Although greater errors (up to 20%) were applied to the wet gas data sets, the effect of the flow measurement errors on the wet gas reservoir model parameters (i.e. porosity and permeability) was seen to be less than their effect on the oil reservoir model. For instance, the largest error in the oil reservoir model parameters was 10.13% which occurred for an estimated permeability based on the data set with 10% systematic and 10% random error. This value in the wet gas reservoir results is just 5.15% for estimated permeability based on the data set with 20% systematic and 20% random error. However, the small errors in the wet gas reservoir model resulted in greater errors in the liquid and gas production forecasts. For example, based on the data set with 20% systematic and 0% random error, 4.92% and 4.04% error occurred for an estimated porosity and permeability respectively, while the error rose to 14.13% for both liquid and gas production forecasts. As a conclusion, although systematic flow measurement errors might not have a significant effect on a wet gas reservoir model, they can affect its production forecasts considerably.

In the results of the wet gas reservoir, no meaningful trend is seen for the change in the parameter errors as a function of random errors. Although for porosity, similar to the results of the oil reservoir, when the random error has increased the effects of the systematic error have dampened, for the other three estimated parameters there is no clear trend in the change of the parameter errors when the random error has changed. The effect of systematic errors in some cases has boosted and in other cases has been mitigated by increasing random errors. This observation is not surprising due to the nature of random errors. However, since the effect of the random errors is not considerable compared to the effect of systematic errors, in many cases it can be ignored without any significant change in the estimated results.

The significant effect of systematic errors on the final parameter estimations and production forecasts for both reservoirs shows the importance of the careful calibration and maintenance of flow meters. As previously stated in the introduction, systematic errors can be prevented if the source of the error is found and eliminated. In contrast to systematic errors, although random errors can be reduced by installing new more precise flow meters, this can be a costly exercise for oil and gas companies. The results of this study suggest that in terms of history matching and reservoir management, replacing current flow meters with new ones might not be the best decision to improve the quality of observed production data. An alternative would be to invest in the regular calibration and maintenance of existing flow meters, which would be a more effective and at the same time more economic decision. In addition to suggesting that regular calibration is valuable, this chapter provides justifications (e.g. the possible cost of errors in history matching) to help in establishing a cash value for that re-calibration in future, hence allowing better management decisions. This cash value may vary substantially for different fields and wells and may also lead to justifications for a different approach such as placing one meter per well, or replacing one type of meter with another, or placing meters on specific high uncertainty wells. It can be an interesting topic for future research studies.

Recalibration and maintenance of flow meters are already undertaken properly by many oil and gas companies based on their production protocols. However, the error in the production data that can affect history matching is not just caused by the flow meters. In many oil and gas fields, production streams of different wells are commingled and only the total flow rate of all wells is measured by flow meters. In these cases, the flow rates of individual wells are estimated by allocation calculations based on the results of occasional flow tests and the total flow rate of all wells. Allocation errors are normally larger than flow meter errors and they can have a more significant effect on history matching. Increasing the regularity of flow tests or installing multi-phase flow meters on individual wells can reduce the systematic and random errors in the production data of individual wells and therefore reduce the uncertainty in the history matching process.

5.1.4 Conclusions

The results of the study clearly show the considerable effect of systematic flow measurement errors on the results of history matching. However, for the simulated oil and wet gas reservoir cases used in this study, the effect of random flow measurement errors on history matching was seen to be insignificant. Although systematic errors can be reduced by more careful calibration and maintenance of flow meters, random errors are normally reduced by replacing an old flow meter with a more precise one that as a consequence entails considerable expense for oil and gas producing companies. However, this study shows that particularly for history matching exercises, reducing random error doesn’t lead to a consequent considerable reduction in the errors in the final results. Therefore, for the case of history matching, this study emphasises the importance of regular calibration and maintenance schedules for existing flow meters as being a potentially more effective alternative to investing in replacing the flow meters with new, more precise ones. Moreover, as the need for calibration is primarily to reduce systematic errors, it is important that the calibration is focussed on the actual operating range of the meter in its installed location.

Based on the results, history matching has been seen to be more sensitive to the flow measurement errors for an oil reservoir than for a wet gas reservoir. However, although the effect of flow measurement errors on the wet gas model parameters (i.e. porosity and permeability) has not been substantial, they have considerably affected the output parameters of the model (i.e. gas and liquid production forecast). In addition, there is normally a significant uncertainty in the production data of wet gas reservoirs due to the difficulty of measuring low fractions of liquid. This study shows that the effect of the uncertainty on the results of history matching for wet gas reservoirs can be noticeable.

5.2 Well testing§

Another main source of information from a reservoir and its production wells is well testing. In a well test (it is also called a pressure transient test) production parameters (mainly production flow rates and well pressure) are monitored for a short period of time (i.e. normally a few tens of hours to a few hundreds of hours) and then the recorded data are analysed to calculate the characteristics of the tested well and the reservoir. Well tests are therefore different from flow tests (flow tests were explained in the previous chapters) although test separators are normally used in both of them. The main difference is that in a flow test the purpose is achieving production flow rates of individual wells while in a well test the recorded pressure data are also analysed in an inverse problem to estimate some parameters of the well and the reservoir.

The information that is provided by well test analysis plays an important role in reservoir management since it is used in simulations, reservoir optimisation and the decision-making process. On the other hand, flow measurement facilities (such as the test separator, single-phase flow meters, or MPFMs) are fundamental elements of well testing systems. Flow measurement uncertainties, therefore, can have an impact on reservoir management and the economic recovery of oil and gas through well testing. Section 5.2 focuses on the impacts of flow measurement uncertainties on well testing and has provided some recommendations on eliminating some of these uncertainties.

5.2.1 Background

The majority of hydrocarbon reservoirs are located under the surface of the earth. It means the only access to the reservoir is through a limited number of drilled wells. Although some reservoir characteristics can be obtained by analysing rock and fluid samples taken from inside the wells, generalising these obtained characteristics based on a limited

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§ The contents of Section 5.2 have been extracted from the following paper with permission from the publisher (Begell House) and the authors:
Marshall, C. D., Sadri, M., Hamdi, H., Shariatipour, S. M., Lee, W. K., Thomas, A. and Shaw-Stewart, J. (2019) 'The role of flow measurement in hydrocarbon recovery forecasting in the UKCS'. Journal of Porous Media, 22 (8).
The candidate contributed to analysing the results, adding literature review and some extra test, and preparing and getting published the article. Other authors developed the methodology, undertook the calculations, contributed to analysing the results, and preparing the final article. The simulations have been undertaken by Hamidreza Hamdi and the results are presented in this section with his permission.

number of samples to the entire reservoir creates a large uncertainty in the knowledge of the reservoir. In other words, even after drilling the wells and starting oil or gas production, the reservoir is still a largely unknown system to us. Therefore, the recorded data from the reservoir during the production period or when well testing is being undertaken is analysed in order to mitigate the reservoir uncertainty through an inverse problem. Using the data, engineers try to gain a better understanding of the reservoir which is a necessary precursor to ensure a good management of the reserves and helps to maximise the economic recovery through increasing the exploitation of the well. Therefore, many articles can be found in the literature that have addressed methods of reservoir uncertainty quantification (Abdollahzadeh et al. 2012; Hajizadeh, Christie and Demyanov 2011; Scheidt and Caers 2009), history matching (Abdolhosseini and Khamehchi 2015; Zeng, Chang and Zhang 2011; Zhao et al. 2016) and well testing (Ahmadi, Aminshahidy and Shahrabi 2017; Bottomley et al. 2016; Hamdi 2014).

The data that is used in all methods developed to reduce the reservoir uncertainty has some uncertainty in itself. The data from a reservoir is measured or estimated using mathematical formulas. Therefore there is always some measurement or estimation error within the data (Lindsay et al. 2017). This error can potentially change the calculated values for reservoir characteristics (e.g. porosity and permeability) and therefore negatively affects the decisions made for the reservoir (e.g. location of new wells and production rates). In other words, the error in the data can indirectly reduce the economic recovery from the reservoir. This issue has not been thoroughly addressed in the literature so far. There is a dearth of literature pertaining to the effect of flow measurement on reservoir performance. Falcone et al. (2001) discussed the benefits and shortcomings of using multi-phase flow meters (MPFM) in oil fields. In their article, they mentioned that in well testing and production allocation, the cost of the operation is reduced by replacing the test separator with an MPFM. MPFMs can also provide real-time continuous data that helps operators to identify sudden changes in the production (e.g. water or gas breakthrough) and react faster. Therefore, using MPFMs can indirectly increase the recovery of oil and gas. Sadri, Shariatipour and Hunt (2017) investigated the effect of flow measurement errors on the production forecast. They performed several history matches based on different sets of observed data with different ranges of measurement error and concluded that flow meters which either overestimate or underestimate the flow rate have a more negative effect on history matching compared to the flow meters that have errors in both directions. Sadri, Shariatipour and Hunt (2018), in a later work (it is presented in Section 5.1), studied effects of systematic and random flow measurement errors on history matching. The results of their case study show that although the effect of random errors are not significant, systematic errors substantially influence the results of history matching.

The aforementioned studies have focused on the role of flow measurement in reservoir management but not specifically through well testing. In Section 5.2 the effects of flow measurement errors on the results of a well test analysis have been briefly investigated. In addition, the possible indirect effect of flow measurement errors on hydrocarbon recovery has been discussed and the impact of accurate flow measurement on maximising economic recovery has been emphasised.

In order to manage a reservoir appropriately, the produced fluids have to be measured accurately. As it was discussed in Section 5.1, history matching is an important exercise of reservoir management that can be affected by the accuracy of flow measurements. Figure 5.1 shows well testing as another element in the loop of reservoir management. This exercise is also sensitive to the accuracy of flow measurement data.

Well testing is typically accomplished by 'flow sampling', through the use of test separators and associated equipment – namely single-phase flow measurement technologies. Well test data is critical to operations in the offshore industry and covers a wide variety of applications. The data can be used to allocate produced fluids to particular wells either directly, or through verification of multi-phase flow meters. The data can also be used in the determination of reservoir size and in the positioning of new wells and installations. Another key use of well test data is in the optimisation of well production where well stream parameters can be altered to maximise hydrocarbon production levels. Recent first-hand audit experience by the UK's Oil and Gas Authority (OGA), however, suggests that well test measurement systems may not be operating near their optimal levels (Oil & Gas Authority 2015). For instance, primary measurement elements (flow meters) are often not removed and recalibrated on a routine basis. There is also evidence of flow meters being exposed to two-phase flows resulting in meter degradation. In addition, the interval between the testing of individual wells may extend to several weeks, with the flow rates between tests inferred by interpolation. The risk is therefore that these measurements may result in a measurement bias or increased uncertainty. Basing reservoir optimisation efficiency and production strategy on measurements where there are fundamental issues that cause unknown levels of uncertainty is clearly not a good practice. As such, mechanisms to provide measurement confidence, such as audits, are in place to ensure compliance.

One of the first comprehensive studies on the analysis of well test pressure responses was presented by Matthews and Russell (1967). Among the other early works that explain the principles of well test analysis in detail are Ramy, Kumar and Gulati (1973) and Earlougher (1977). Numerous studies have been published with a focus on specific methods of well testing and their advances. Build-up (Barbe and Boyd 1971; Foster, Wong and Asgarpour 1989; Hegeman, Hallford and Joseph 1993) and draw down (Chase 2002; Khosravi and Ketabi 2014) tests have been the most common methods addressed in the literature. In a build-up test, a producing well is shut in and then the downhole pressure change is recorded over time and analysed. In a draw down test, the downhole pressure change is measured for a well that is initially (or after an extended shut-in period) brought into production. Many other techniques of well testing, such as the drill stem test (DST), production test, multi rate test, and interference test, have been presented in the literature. More details about different well test methods have been presented by Stewart (2011).

A basic well test system consists of a subsurface string, incorporating downhole tools such as gauges, check valves, flow switching valves, isolation valves and packer assemblies, together with a surface or deck system for separating, sampling and metering the fluids flowing from the well. A detailed explanation of the operational aspects of well testing has been presented by McAleese (2000). Well tests mainly incorporate estimating some reservoir properties such as reservoir size or reservoir storage capacity. They are used to obtain dynamic data from a reservoir during different stages of the life of that reservoir. It therefore, affects decision-making regarding further development. Well testing objectives are diverse and can be used to confirm the existence of hydrocarbon fluids in the drilled wells, to obtain downhole samples and to characterise the reservoir. The duration of a typical well test is usually short, of the order of tens or hundreds of hours. The main well test deliverables that can influence maximising economic recovery

(MER) and will be discussed further in Section 5.2 are reservoir parameter characterisation, reservoir model selection, and production flowrate determination.

These three deliverables link closely to MER through reservoir optimisation and the ability to maximise the recovery factor for the well. Typically, a reservoir characterisation is achieved by finding a model that matches the empirical data which can provide the well characteristics, such as flow capacity (i.e. permeability-thickness product), skin factor, and the structural and/or hydrodynamic boundaries.

The ultimate goal of either test is to describe a reservoir such that it can reproduce the same output for a given input signal. Therefore, because well testing is effectively an inverse problem - one which needs the data to match the model - its interpretation largely depends upon the quality of input and output data. Hence, the focus of the study is on investigating the role of measurement uncertainty upon MER.

5.2.2 Methodology

The focus of the work lays in running a number of simplified models in order to explore the importance of rate measurement for well test interpretations; as opposed to developing in-depth models akin to those in use commercially. The scope of the study encompasses downhole rate measurement as a necessary means of comparing and contrasting such measurement with surface techniques. The modelling intends to establish, in broad terms, the nature and strength of the link between the uncertainty in the surface well test measurement and its importance in maximising future extraction.

In order to successfully optimise production from a particular well, the well itself has to be characterised so that its future production can be accurately modelled with a low uncertainty. Only once production has been predicted can the most optimum production pattern be obtained. There are two parts to this prediction, namely the characterisation of the parameters within the well/reservoir itself e.g. porosity, permeability, skin factor, etc. and the model used to calculate the outputs given the input parameters. Both of these parts are determined through data collected from the well tests. Traditionally, surface flow measurements have been a key component in the analysis.

In this work, an example reservoir was created and a series of sensitivity runs were conducted to assess the output from the example with respect to the changing input parameters. The example reservoir was based on a typical 100 ft vertical well within a cylindrical fractured reservoir with an outer radius of 5000 ft (1524 meters). A fractured model was chosen as the reference model in this work because it provides the opportunity to investigate the effect of flow measurement errors on more reservoir parameters compared to a sandstone model. The values for the other parameters of the reservoir are shown in Table 5.4.

Table 5.4: Characteristics of the simulated reservoir

Storativity ratio (ω)	Inter-porosity flow coefficient (λ)	Permeability (K)	Bulk porosity (S)
0.1	2 E-6	500 mD	0.27

Storativity ratio is the fraction of total porosity associated with fractures and inter-porosity flow coefficient is the ratio of the permeability of the matrix to the permeability of the fracture. The parameters can be taken as descriptors of how fluids flow through a reservoir and their definitions can be found in various sources such as (Lee 1982; Terry, Rogers and Craft 2013; van Golf-Racht 1982). However, for the purpose of this study they can be thought of as inputs to a model where the closeness of the predicted values of these inputs to the actual values dictates the accuracy of the model as a whole.

During each test run, the example reservoir was 'produced' with varying levels of measurement information recorded and utilised. This measurement data was then used as a disturbing signal to generate the pressure data and the predicted reservoir parameters using the transient well test interpretations. In other words, we try to investigate how the measurement error can lead to a completely different well test interpretation for similar models with exactly the same parameters. A comparison could then be made between the accuracy of the model and correct parameters in the example reservoir. The test runs consisted of a single-phase oil drawdown at a constant flow of 9200 STB/D with a duration of 158 hours. Then the well was shut-in for 8 hours for a build-up phase before being produced again.

The second stage production could be applied for any time frame and for these tests the well was assumed to produce for 20 years allowing for a direct comparison of cumulative production i.e. how much total hydrocarbon was recoverable over the timeframe compared with values obtained during other test runs. This then allows a comparison as to which methodology allows for maximising recovery factors, and hence MER.

The test runs considered during these tests were:

1. Correct flow rate measurements taken at the surface (well head)
2. Correct flow rate measurements taken downhole
3. 10% random error in flow rate measurement taken at the surface
4. 10% random error in flow rate measurement taken downhole

The purpose of defining the scenarios is to generally show the effect of random flow measurement errors on the calculated hydrocarbon recovery.

The well test scenario in this work includes a draw down (DD) and then a build-up (BU). This scenario is similar to the reported well test by Meunier, Wittmann and Stewart (1985) but in a fractured environment.

5.2.3 Results and discussion

The monitored production flow rates for test runs 1 and 2 are different, particularly at the transition between drawdown and build-up. This is due to the fact that once the well is shut-in, there will be no flow at the surface. However, with downhole measurement, once the well is shut-in the reservoir still flows until it reaches an equilibrium where there is a pressure balance and the produced area becomes stable again. Surface flow rate measurements do not record this additional flow post well shut-in and therefore do not include them in parameter predictions which can cause an error as shown in Figure 5.7a and 5.7b.

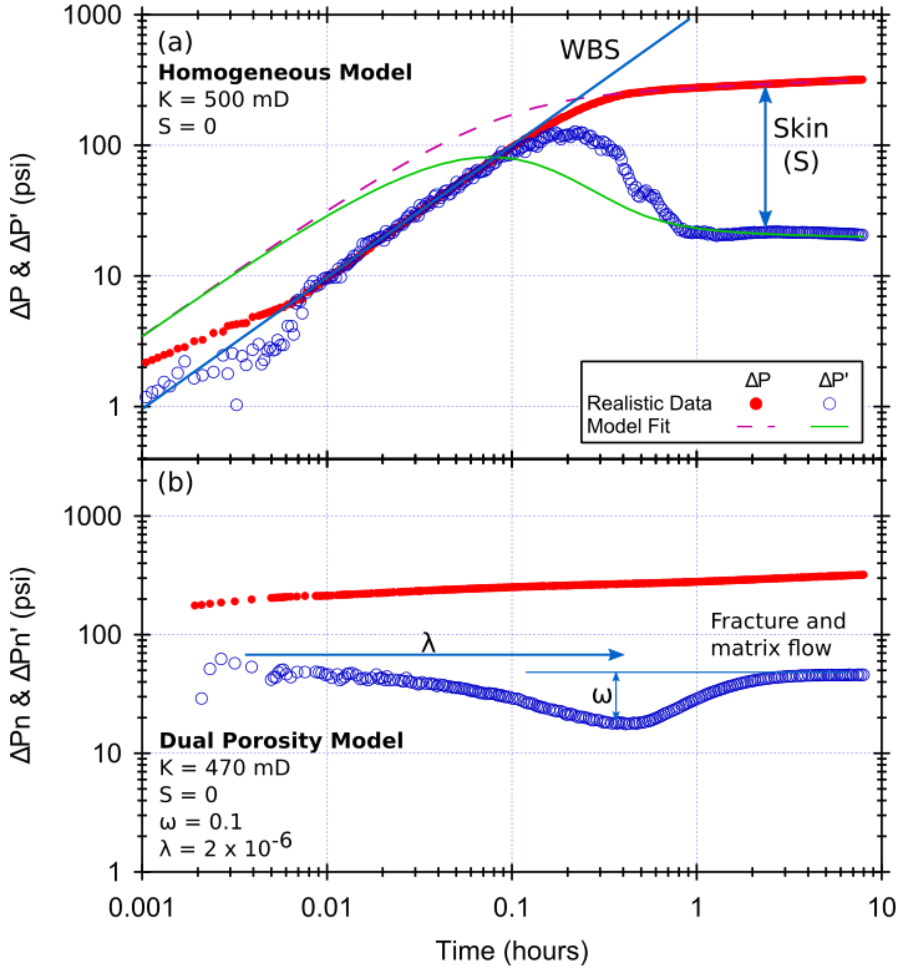

Figure 5.7: Well test diagnostics plot for synthetic test run 1 with standard (a) surface flow metering and test run 2 with (b) downhole flow metering (Marshall et al. 2019)

Figure 5.7a and 5.7b show the well test log-log diagnostic plots for test runs 1 and 2 respectively. The shape, slopes, and plateaux of the curves found on a well test diagnostic plot are used to estimate parameters to describe a reservoir which will be used in a reservoir model.

The curves in Figure 5.7a and 5.7b describe the same reservoir but Figure 5.7b conforms to a significantly different model than Figure 5.7a. The Y axes of the plots are different merely because when variable rates and pressures are employed, as for the case with downhole measurements, the well test theory requires the use of a superposition function to be able to plot the data on the specialized plots, such as log-log plots, and subsequently analyse them. This is based on fundamental well test theory for multi-rate/pressure cases. For a simple case with one draw down and one build-up this function will be reduced to a case where we have ΔP (pressure difference) and ΔP' (derivative of pressure difference). More information about the superposition function can be found in well test literature that provides the fundamental theory of well test data analysis under variable and/or single rate change scenarios such as Bourdet (2002) or Houzé et al. (2015). Figure 5.7a is related to the case when the variable rate is ignored and only one draw down and one build-up are considered. However, in Figure 5.7b the variable downhole rate measurements have been implemented.

The results in lower modelling uncertainties and better prediction capability, suggesting that for MER, surface flow rate measurements are not the best method of measurement available. Figure 5.7a denotes an area as wellbore storage (WBS) on the curve. This is an effect that masks well flow rates from surface flow rate measurements through essentially a dampening effect. Owing to the distance, pressure differential and other factors, the production profile at the well perforations and any associated pulsations or changes in component fractions at these points will be 'smoothed' out as the fluids flow to the production platform. What could have been a high pressure region or high water cut region will be averaged out by the rest of the fluids, meaning the information will be lost. This is shown in Figure 5.7a. Again, it is important to point out the data itself is used to help choose the subsequent correct model to use.

For test runs 3 (surface measurement) and 4 (downhole measurement) a 10% error was introduced into the flow rate measurements to assess the impact of these errors on the estimated recovery factor of hydrocarbons. It was found that a 10% flow rate measurement error resulted in a 17% permeability estimation error. The location of the flow rate measurements (surface or downhole) did not impact this relationship. The calculated parameters for test run 2 (no error downhole measurements) and 4 (10% error downhole measurements) are compared in Table 5.5.

Table 5.5: Parameters calculated based on test runs 2 and 4

Parameter	No error in downhole rate (test run 2)	10% error in downhole rate (test run 4)
Permeability	470 mD	550 mD
Wellbore storage	0.24	0.07
Storativity ratio (ω)	0.1	0.1
Inter-porosity flow coefficient (λ)	2E-6	2E-6

ω and λ have the same values in test runs 2 and 4, as shown in Table 5.5. This can be because both parameters are ratios between quantities associated to the matrix and fracture, as defined in Section 5.2.2. Hence, if the estimated quantities for the two aforementioned media change to the same extent due to the flow measurement errors, their ratios remain the same. These parameter errors, however, were not found to have a significant effect on the estimated recovery factor. As an extreme case, when the flow rate error (or equivalently the resulting estimated permeability) is ±50% under the conditions in the example reservoir, the recovery factor after 20 years was found to have only a 3% error. It should be noted that the effect of permeability is on the accelerated recovery i.e. the speed at which the reservoir is producing oil, not on the ultimate recovery (Lake and Walsh 2003). It should also be added, however, that in this work, only the effect of random errors has been investigated. In reality, flow meters may also have bias errors in addition to their random errors as it was discussed in Section 5.1. In most cases, random errors have a normal distribution in both the positive and negative direction. Therefore, they cancel out or dampen the effect of each other. In contrast to random errors, bias (systematic) errors are mostly distributed in just one direction (positive or negative). As a result, if the effect of systematic errors is considered, the results may be completely different. However, while the effects of systematic errors are widely appreciated in the industry, the effects of random errors are sometimes ignored. Therefore, in this section the potential significant effects of random errors have been analysed and emphasised.

As discussed earlier, there are two elements in reservoir prediction necessary to optimise production successfully. The main impact on MER from flow rate measurement errors is not from the reservoir parameter estimation but from the use of the data to select the most appropriate model. For each test run, the data generated on reservoir parameter estimations and the most appropriate reservoir model were used to ‘produce’ the example reservoir for a period of 20 years. For test runs 1 and 3 a single medium model was selected since it was the best match to the data and for test runs 2 and 4 a dual medium model was selected for the same reason. Dual medium denotes a reservoir fracture being detected whereas single medium denoted no fracture. For all four cases the final recovery of the reservoir was estimated. The results show that the model uncertainty has a higher impact on the estimated final recovery compared to the reservoir parameter (e.g. permeability) uncertainty. For the single medium and the dual medium models the estimated recovery factors are 31.2% and 35%, respectively. Using a single medium model, therefore, the reduction in the estimated recovery factor is around 12% compared with the dual medium model. Potentially this could be a huge number in terms of an estimation of reservoir economics.

The model and parameter uncertainties which are caused by flow measurement errors not only affect the estimated recovery factor but also the actual one. Since the model and the parameters are used in simulations and reservoir optimisation then the results are employed to make decisions about the reservoir (e.g. deciding about production rates and locations of new wells). The uncertainties caused by flow measurement errors indirectly affect the actual performance of the reservoir and the recovery factor. Therefore, they influence MER.

5.2.4 Conclusions and recommendations

As the study shows, the use of downhole flow rate measurements can provide additional information on well flows that is not available from surface measurements. Wellbore storage issues affect all surface flow rate measurements to some degree resulting in dampened measurement results that can induce inaccuracies. Downhole flow rate measurements, on the other hand, are the most valuable sources of information for MER as they provide real-time, continuous, and undampened reservoir responses. This provides the most accurate and useful data for reservoir engineers in production optimisation. In terms of the effects of measurement errors on reservoir parameter estimation, it was found that there is a weak link to the estimated recovery factor. Instead, the largest contributor to the estimated and actual recovery factor from measurement is when the well test data is used to select a reservoir model. This means that the typical estimated uncertainties seem to be acceptable in terms of measurement requirements, as long as the reservoir model is correct.

Chapter 6: Conclusions and recommendations

6.1 A summary of the results

In this thesis, the direct and indirect effects of flow measurement uncertainties on the economic recovery of oil and gas reservoirs through hydrocarbon accounting and reservoir management were investigated. The role of flow testing on the accuracy of allocation calculations, which is still the most common method of well flow rate estimations in the oil and gas industry, was firstly studied in Chapter 3. In this chapter, the effect of increasing the frequency of flow tests on the estimated total production of wells, allocation, and hydrocarbon accounting was evaluated. Allocation calculations were undertaken for three different cases using actual and simulated production data based on one to four flow tests per month. Allocation errors for each case were subsequently obtained. The results showed that for all the investigated cases, the average allocation error decreased when the number of flow tests per month increased. The sharpest error reduction was observed when the frequency of the tests increased from one to two times per month. It reduced the allocation error for the three investigated cases by 0.43%, 0.45%, and 1.11%, respectively, which are equivalent to \$18.2M (Million), \$18.9M, and \$46.8M reduction in the yearly cost of the allocation error for the respective cases. The reductions in the allocation error cost for the three cases were \$27M, \$29M, and \$80M, respectively, when the flow tests were undertaken weekly instead of monthly. Although the results of Chapter 3 showed a higher frequency of flow tests can potentially increase the accuracy of the allocation process, the question remained as to the minimum number of flow tests necessary to reduce the error of the allocation data to less than a desired value. In Chapter 4, a machine learning technique was employed to achieve this aim. An artificial neural network was trained to find the relationship between the statistical characteristics of the production data of oil wells and the minimum number of flow tests a month required for each well to secure an estimate of the production data within a target error specification. The results showed that the accuracy of the estimations of the network is higher when its target is the average error of the entire field rather than the error of its individual wells. For an error specification of 5%, over 99% of the estimations were found to be correct when the target was the field error. The accuracy for the same error specification was 60% when the target was chosen to be the error of individual wells. For both cases, although the estimations exhibited good accuracy in larger error specifications, this accuracy decreased when the target error specification was reduced. The research results, however, show that the application of a neural network can have a significant effect on reducing allocation errors when considering the large uncertainty associated with an allocation process.

To gain a better understanding of the effects of flow measurement uncertainties on the economic recovery of oil and gas, Chapter 5 of the thesis was dedicated to studying their effects on two main tools of reservoir management, namely history matching and well testing. In the first section of Chapter 5, the effects of systematic and random flow measurement errors on history matching were investigated. Initially, 14 production data sets with different ranges of systematic and random errors, from 0% to 10%, were employed in a history matching exercise for an oil reservoir and the results were subsequently evaluated based on a reference model. Subsequently, 23 data sets with errors ranging from 0% to 20% were employed in the same process for a wet gas reservoir. The results showed that for both cases systematic errors considerably affected history matching, while the effect of random errors on the considered scenarios was seen to be insignificant. Although reservoir model parameters in the wet gas reservoir were not as sensitive to the flow measurement errors as in the oil reservoir, for both cases the future production forecast was significantly affected by the errors. Permeability was seen to be the most sensitive history matching parameter to the flow measurement errors in the oil reservoir, while for the wet gas reservoir the most sensitive parameter was the forecast of future oil and gas production. Finally, considering the noticeable effect of systematic errors on both cases, it was suggested that flow meter calibration and regular maintenance be prioritised, although the subsequent economic cost needs to be considered.

The second section of Chapter 5 focused on the role of analysing flow measurement errors in well testing. The impacts of the location of the flow meter (downhole or on the surface) and the existence of random errors (0% or 10%) on the estimated recovery factor of a simulated reservoir were investigated. As the results of the case study showed, although random errors had a small direct effect on the estimated recovery factor, they could have a significant indirect effect on it by misleading to the choice of a wrong reservoir model. The research results also suggest that downhole flow measurement data are more valuable than the surface data since downhole data eliminates the well bore storage effect.

6.2 Concluding remarks and recommendations

The results of this research show the significant importance of the availability of real-time continuous flow measurement data. Having it reduces uncertainty, improves reservoir management and decision making, enables more accurate and fairer hydrocarbon accounting calculations, faster reactions to sudden production changes, and finally increases the economic recovery of oil and gas. Installing MPFMs on individual wells, hence, is highly recommended where it is financially and technically feasible. In the cases where installing MPFMs is not feasible, however, it is still essential to make sure that the uncertainties in the production data measured or estimated based on flow tests are in an acceptable range. It was shown in this research that in such cases undertaking a proper data analysis and increasing the frequency of flow tests can have a substantial effect on the accuracy of the data and the results of the allocation calculations, therefore, increasing the economic recovery of oil and gas. Employing data science and machine learning techniques was shown to be promising in finding the optimum frequency of flow tests needed to achieve estimations within the desired error range. The analysis showed the significant effect of systematic errors on history matching and reservoir management. On the other hand, it was shown that even the effect of random errors on hydrocarbon accounting and well testing can potentially be large. Sticking to the aforementioned recommendations, in addition to regular calibration and the maintenance of flow meters can help in eliminating them.

6.3 Recommendations for future work

Despite all the aforementioned benefits of MPFMs for the oil and gas industry, some challenges remain for those oil and gas companies that want to install them on their wells. If the MPFM is intrusive, they need to shut down their well during the installation process that can be considerably costly. Although different non-intrusive MPFMs have successfully been developed by different companies and individuals recently, they have proven to be less accurate in some applications. Another challenge in the application of MPFMs is their capital cost. Their capital cost, in addition to the cost of their regular calibration and maintenance, can still dissuade oil and gas companies from using them. More work on developing affordable accurate nonintrusive MPFMs that can work under the range of operating conditions that is seen in the oil and gas industry is deemed necessary. On the other hand, parallel to developing better MPFMs, it is worth working on improving the application of data science and machine learning in flow rate estimations and optimising flow measurement systems and procedures. A method based on an ANN was presented in this work. The accuracy of this method can potentially be improved by adding other inputs to the network or the same approach can be used in mitigating flow measurement uncertainties of the data coming from other sources, except allocation, such as flow meters or VFMs.

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